The economics of financial information in young firms

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A l'Alba, la Bruna, l'Agnès, l'Albert i la mare

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Summary

This thesis focuses on the use of accounting information to mitigate the severe information asymmetries existing between young firms and capital providers. The first chapter studies the importance of debt in early stage financing activities. In particular, I find that debt, and especially business debt, can serve as a reliable signal to attract outside equity investors, mainly through a disciplining governance mechanism that debt imposes into the firm. In the second chapter, I study the relevance of accounting information in recently public firms. Using a recent US disclosure deregulation, I show that firms that more significantly reduce the amount of information in their annual reports experience a stronger decline in the market reaction to their earnings announcements. Finally, in the third chapter, I find that entrepreneurs' personal characteristics affect their information preparation processes and firm outcomes, with more passionate, dominant, and attractive entrepreneurs showing higher financial forecast errors but yet higher likelihood of being invested.

Resum

Aquesta tesi es focalitza en l'ús de la informació comptable com a eina per reduir la informació asimètrica existent entre empreses joves i proveïdors de capital. El primer capítol analitza la importància del deute en rondes de finançament inicials. En concret, demostro que el deute, i especialment el deute en nom de l'empresa, pot servir com un senyal fiable per a l'atracció d'inversors de capital, primordialment degut als mecanismes de governança que el deute imposa a l'empresa. En el segon capítol estudio la rellevància de la informació comptable en empreses que surten a borsa. Emprant una recent desregulació comptable als EE.UU mostro com aquelles empreses que redueixen més significativament el volum d'informació proporcionat als seus estats financers experimenten una reducció en la reacció dels mercats de capital als seus anuncis de resultats. Finalment, en el tercer capítol estudio com característiques personal de l'emprenedor tenen un efecte en la informació que aquests preparen i reporten, així com en certs resultats empresarials. En concret, demostro com emprenedors més passionals, dominants i atractius generen errors més grans en les seves projeccions financeres, tot i que tenen més probabilitats de ser invertits.

Preface

In this thesis I explore the use of accounting information to mitigate the severe information asymmetries existing between young firms and capital providers. In particular, this dissertation examines the role of accounting information in young firms' financing activities and disclosure choices. Overall, my research has been influenced by the work of scholars such as Cassar, Davila, Foster or Hand among others, who brought together the fields of accounting and entrepreneurship in the early 2000s. The context featuring the dot-com bubble explosion propelled this line of research, which continues to be relevant due to new technological advances (e.g. big data or blockchain) and new forms of financing (e.g. crowdlending or Initial Coin Offerings) that are many times initiated in these small young companies. This preface places the above research line into the three chapters that form my dissertation, and puts them in a broader academic, intellectual and even personal context.

In chapter 1 of the dissertation I explore debt as one of the information channels that young firms use to attract early stage equity investments. This chapter is a joint work with Mircea Epure and follows from my master thesis. We document a positive association between debt, and in particular business debt, and equity financing. We posit that outside investors can attempt to identify when an effective governance is already in place, and see debt as a governance mechanism that tightens management discretion over future cash flows, directs entrepreneurs towards a more professional market oriented management, and can ultimately shift the control of firm management if conditions require it. Altogether, we argue that debt becomes more than a simple financing tool towards firm growth, and acts as a mechanism that raises accountability and transmits valuable information to outside investors.

While Chapter 1 implicitly assumes financial and non-financial information disclosure to investors, it does not explicitly analyze firm disclosure. In chapter 2 (my job market paper), I use the IPO setting to study investor's reaction to a reduction in the amount of information conveyed to the market. This work was initiated during my stay at the University of North Carolina and has benefited from talks with Wayne Landsman and Javier Gómez, my second supervisor, upon returning to Barcelona. In this chapter, I exploit a recent US disclosure deregulation (the JOBS Act) to analyze whether accounting information remains as informative after relaxing mandatory disclosure requirements. Results show that after the Act, only those firms that reduce their public

disclosure experience a decline in the market reaction to their earnings announcement event. I document that this decline does not only originate from the reduced mandatory disclosure, but also from an increased voluntary disclosure in the months preceding the earnings announcement. This result provides evidence of a substitution effect from mandatory to voluntary disclosure, which may give insights to regulators on the ongoing consideration of reducing disclosure requirements.

Chapter 3 turns back to the information channels young firms use in early stage financing activities. In collaboration with Antonio Davila, we argue that perceptions of entrepreneurs' personality traits can be one vehicle through which early stage investors can ex-ante integrate entrepreneurs' behaviors and actions. We study how investor perceptions of entrepreneurs' personality traits relate to firm reporting practices (i.e. financial projections errors and firm overvaluation) and economic outcomes more generally (firm survival and actual equity investment decisions). In particular, we show that presence (a component capturing passion, dominance and openness in gestures) and attractiveness correlate with higher financial forecast errors, higher firm overvaluations, lower rates of survival, yet higher likelihood of receiving outside funding. We posit that understanding the effects of personal characteristics in a timely manner can be useful to early stage investors in the assessment of investment opportunities, deal structure (e.g. contract design), and ex-post monitoring. Altogether, our study complements the set of available ex-ante information that early stage investors can use to mitigate potential business model uncertainties and (ex-ante) information problems. This project developed alongside the other two chapters, as I devoted extensive time to the manual collection of data from the IESE Business Angels Network, to whom I am grateful for sharing their information.

Contents

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Chapter 1

1. Debt Signaling and Outside Investors in Early Stage Firms

Joint with Mircea Epure

1.1 Introduction

The increasing supply of private equity investments positively affects firm creation, employment, and aggregate income (Samila and Sorenson 2011). Attracting external financing is especially critical for early stage firms, which face different constraints as compared to incumbent firms (e.g. recurrent cash flows and retained earnings are usually not available). While debt is the prevalent financing source at the early stages of the firm (Robb and Robinson 2014), outside equity injections can be attractive to entrepreneurs due to their positive impact on firm growth (Croce et al. 2013; Puri and Zarutskie 2012) and management practices (Davila and Foster 2007).

The uniqueness of start-up characteristics and the stringent informational asymmetry in their context (Arthurs et al. 2009; Cassar 2004; Cassar et al. 2015) require taking a step beyond the usual approaches to firm capital structure. In the case of incumbent firms, the accounting literature indicates that investors may prefer firms with lower debt levels (Caskey et al. 2012; Jones and Hensher 2004), while finance studies point to a pre-established order of financing sources (Myers 1984). However, in an entrepreneurial context investors face a higher informational risk, which may magnify the role of early stage financing.

We posit that debt can be a reliable signal for outside equity investors, by alleviating the information asymmetries that are tightly woven into the expected governance tensions in

entrepreneurial firms. One key tension is that, subsequent to receiving an outside investment, firms can engage in moral hazard behavior by pursuing private benefits. This largely explains why equity investors in entrepreneurial firms institute stricter management control systems (Davila and Foster 2007). Contrasting with an ex post behavior focus, we propose that outside investors can attempt to identify early stage firms which already feature governance mechanisms that help to mitigate potential agency conflicts. Debt, which is usually present at early stages (Robb and Robinson, 2014), can reduce misaligned incentives by imposing a disciplining governance mechanism (Jensen 1986). To be effective, such governance should also direct entrepreneurs towards a more professional market oriented management, rather than the commonly observed personal management (Bloom et al. 2012).

We thus conjecture that outside investors can rely on the signaling value of debt that is given by its effective governance role. Foremost, debt enacts a market like governance (David et al. 2008; Williamson 1988), with strong implications on firm control (Kochhar 1996). The governance of the control rights behind debt can be tied to the monitoring of cash flows (Jensen, 1986), but can go as far as fully shifting the control of firm management (Grossman and Hart 1982), which entails a magnified impact in the case of entrepreneurs. Given the dire consequences of not repaying debt, this financing source becomes more than a simple alternative for lifting roadblocks towards firm growth, and acts as a governance mechanism that raises accountability and can transmit valuable information to outsiders.

Moving beyond the main relationship between debt and outside equity, we uncover various layers of heterogeneity at firm and industry levels. First, we hypothesize that the signaling value of the firm's business debt is higher relative to that of personal debt, which is granted to the entrepreneur instead of the firm. Business debt is observable in financial statements and has costlier underpinnings: it entails higher screening and monitoring costs, and lenders institute an ongoing governance and control mechanism even in times of good economic prospects (see, e.g., Dey et al. 2016; Triantis and Daniels 1995). Such arguments become stronger for bank business debt, as specialized lenders can have additional advantages based on soft information from an early bank-firm relationship and the active monitoring of funding sources such as credit lines (Berger et al. 2017; Degryse and Ongena 2005). Second, we link the intensity of the debt signal to the interaction between the governance mechanism instituted through business debt and the unlimited liability of the entrepreneur's personal debt with the firm. With high levels of business debt and in the presence of personal debt, the entrepreneur is not only accountable to external constituents who actively monitor firm activity, but also signals commitment with the firm and thus enhances the reliability of the

signal to outside investors. Third, we hypothesize that the governance role of debt can send a stronger signal to outside investors in capital intensive industries. Accordingly, lenders can institute a more effective governance mechanism in capital intensive industries that feature more reliance on financing needed to scale up their business models (Gompers and Lerner 2002; Rajan and Zingales 1995).

We test our theoretical predictions using the Kauffman Firm Survey (KFS), which provides a panel of US firms that were founded in 2004 as new independent businesses and tracks them during seven follow-up years. Our empirical strategies account for selection into outside equity financing, compare similar firms that only differ in debt levels at inception, and mitigate endogeneity concerns related to confounding factors that could drive debt and equity. We consistently find a positive relationship between debt and outside equity injections. This positive association is stronger for business debt and bank business debt. It is also more pronounced when business and bank business debt are accompanied by personal debt, when the firm has a bank credit line, and in high capital intensive industries. In granular results, we show that debt effects are stronger in times of economic distress, when capital providers may rely more on available signaling. Finally, we uncover real effects by showing that high debt firms achieve higher growth (but not higher profitability), which is stronger in the case of business debt and in capital intensive industries.

Our contributions are multifold. We fill a gap in the literature by probing into the relationship between debt and outside equity at the early stages of the firm. Existing studies on capital structure largely refer to incumbent firms, perhaps due to their market shares or the scarcely available data on start-ups (especially from the US). We start from the pervasive opaqueness of both the entrepreneurial firms and the financing process, and propose a theoretical framework of the governance role of debt which can produce an observable and costly to reproduce signal on which outside equity investors can rely. The basic premise is that the presence of lenders can provide informational benefits due to their early stage screening and especially due to the governance mechanisms they impose. Such market like governance directs entrepreneurs towards more rigorous management practices, and can help investors to assess arm's length equity transactions.

Our framework and empirical results contribute to a vibrant stream of literature that employs signaling rationales to understand the entrepreneur-investor relationship (e.g. Ahlers et al. 2015; Arthurs et al. 2009; Baldenius and Meng 2010; Conti et al. 2013; Davila et al. 2003; Downes and Heinkel 1982; Islam et al. 2018; Pollock and Gulati 2007). We push a step further the literature on the importance of the early stage capital structure for the investors'

selection process, in which financial information (e.g. Armstrong et al. 2006; Hand 2005) and non-financial information such as owner characteristics (e.g. Baum and Silverman 2004; Bernstein et al. 2017; Dimov and Shepherd 2005; Maxwell et al. 2011) have been shown to matter. By focusing on the governance mechanisms that debt imposes, we help to reduce attribution errors that investors can make (Baum and Silverman, 2004). Finally, we contribute at the intersection of theory and empirics by juxtaposing the roles of the financing structure and owner characteristics.

Our work also paves the way to implications for entrepreneurs and policy makers. In managerial implications, we show that entrepreneurs could rely on the governance role of debt to signal accountability to external constituents through the early stage bank firm relationship. In policy implications, we discuss that early stage debt can hold a higher signaling value in more capital intensive industries. In these contexts, there should be fewer regulatory interventions, as investors can rely more on firm and entrepreneur-level signals. In contrast, the signal holds a lower value in less capital intensive industries, especially if these are emerging industries, and regulators could strategically consider to intervene, e.g., via competitive financing programs.

1.2 Theoretical framework and hypotheses

1.2.1 Outside equity in early stage firms

Outside investors range from individuals, the so-called business angels (BA), to companies, government agencies, and institutionalized venture capital (VC) firms. Market based equity financing, present in fewer firms as compared to debt, is most common in the venture cycle of US entrepreneurial firms (Gompers and Lerner, 2002) than in other contexts which feature more bank-dependent financing of entrepreneurship (Colombo and Grilli 2007; Jeng and Wells 2000). Illustratively, in 1980, the US VC industry invested $610 million in business projects (Puri and Zarutskie 2012), while in 2016, investments amounted to $61 billion, with a peak of $105 billion in the 2000 dotcom bubble.[1] Given the US context of our study, we examine outside equity investments that are related to the start-up year and subsequent growth and expansion stages (see, cf., Gompers and Lerner, 2002; Jeng and Wells, 2000). This is consistent with the Kauffman Firm Survey design and Robb and Robinson (2014), in which

[1] See the 2017 PwC MoneyTree Report on the historical trends in private equity.

the capital structure decisions of new firms are tracked starting with the founding year for a period that allows for observing investment and growth outcomes from initial decisions.

Outside equity can be a key financing source, with important implications for the financing (Chemmanur and Fulghieri 2013), management practices (Davila and Foster, 2007), and survival and growth (Davila et al., 2003; Puri and Zarutskie, 2012; Croce et al. 2013) of early stage firms. The debate on the relationship between early stage debt and equity remains open, mostly due to the opaqueness of both the entrepreneurial firms and the investors involved in the financing processes. Previous studies find that both non-financial and financial information can be relevant attributes for investor decisions. First, there is a general consensus on the importance of intangible attributes such as owner characteristics or industry expectations in earlier (MacMillan et al. 1987; Tyebjee and Bruno 1984) or more recent work (Baum and Silverman 2004; Bernstein et al. 2017; Dimov and Shepherd 2005; Maxwell et al. 2011; Sorensen 2007). Second, financial information can play a role in outside equity injections. For instance, Armstrong et al. (2006) study how financial information can explain pre-IPO differences in equity valuations, while Hand (2005) shows that cash holdings are positively related to equity valuations. Overall, there appears to be a complementarity between the two types of information, and using the relevant variables can help to overcome attribution errors that investors have been shown to make (Baum and Silverman, 2004).

Whereas we analyze the factors influencing investors' decisions, we will carefully consider the implications of outside investor presence. In start-up firms there is no clear separation between ownership, management and control, as many times entrepreneurs engage in all tasks. Incoming outsiders who hold significant equity may reshape the power distribution, decision-making and control. For instance, they tend to institute formal organizational practices related to human resource policies, the adoption of stock option plans (Hellmann and Puri 2000) or management control systems (Davila and Foster, 2007). This could clash with the entrepreneurs' personal style of managing the business, while a more market oriented management practice may serve to attract outside investors. We address related issues in the next section and in setting-up the analysis

1.2.2 Information asymmetry and the relationship between debt and outside equity

Early stage outside investors face particularly opaque ventures and consequently a high information risk. Given that they cannot rely on past information or market valuations, investors must identify reliable information signals of firm characteristics.

If new ventures were to behave similarly to incumbents, the relationship between debt and outside equity would follow established accounting or finance insights. First, the accounting literature indicates that high debt could be informative of financial distress (Caskey et al., 2012; Jones and Hensher, 2004), and thus one would expect early stage debt to send a negative signal to investors. Second, in corporate finance, the pecking order theory posits that an incumbent firm may choose to finance operations first through internal financing and, only after, through debt financing and ultimately, through equity markets (Myers, 1984). This would imply that firms have unequal willingness and possibilities to access debt depending on their existing debt levels, and that the preference for a certain financing source supersedes the potential usefulness of that source to mitigate information asymmetry problems. Robb and Robinson (2014) document that the pecking order theory may not apply to start-ups. As we will argue, this can be due to a signaling value in the governance role of debt that can supersede a pecking order logic.

Signaling theory has been widely used to study the opaque entrepreneur-investor relationship (Arthurs et al., 2009; Cassar et al., 2015). In an early study, Downes and Heinkel (1982) show that entrepreneur ownership can positively link to firm value. More recently, Baldenius and Meng (2010) and Conti et al. (2013) theorize on how signals may lead to different investor efforts depending on contract and firm characteristics. Their results are in line with Elitzur and Gavious (2003) who show that the negotiation between entrepreneurs and investors is a reliable signal of fewer potential moral hazard problems. Arthurs et al. (2009) argue that the length of pre-IPO lockup periods can be a signal of firm quality, and Pollock and Gulati (2007) link IPO signals to alliance formation. Sanders and Boivie (2004) highlight governance characteristics as useful signals; Ahlers et al. (2015) point to human and intellectual capital as uncertainty reduction factors; Davila et al. (2003) state that VC funding events help to signal the quality of the firm in the labor market; and Islam et al. (2018) show that research grants are a useful signal for attracting VC funding.

We argue that debt can serve as a signal of an effective governance mechanism to mitigate information asymmetry between entrepreneurs and investors. Entrepreneurial firms

can generate the debt signal through the joint process of applying for debt and having the application approved by the lender. Once produced, this signal is credible since it fulfills the observability and costliness conditions (Connelly et al. 2011; Spence 2002). First, debt is observable in the financial statements of the firm. Second, it is costly to produce since its contracting has to adhere to various conditions, including screening processes and subsequent monitoring. This enacts the lender as a gatekeeper and ex post monitor, and thus should ensure that entrepreneurial firms unable to obtain debt—either due to the application process or failure of committing to contractual conditions—cannot falsely introduce noisy signaling in the environment. Such characteristics are more common to a separating equilibrium, in which only willing and able firms can signal through debt, rather than a pooling equilibrium in which outside investors would not be able to distinguish between entrepreneurial firm types.

The role of debt as an effective governance signal is supported by both agency theory and transaction cost economics. Jensen (1986) uses agency rationales to argue that debt disciplines managers' use of cash flows and generally limits discretion over payout policies. Williamson (1988) explains through a transaction cost economics perspective that debt governance is important when assets are redeployable, such as the case of cash, which is key in entrepreneurial firms that feature less professional management and the pursuit of private benefits. Examining the two theories together, Kochhar (1996) describes the tensions related to the capital structure of the firm and how debt can ease potential conflicts by imposing an effective governance with implications on the control rights of the firm. This type of governance is similar to the management control systems that outside investors tend to impose after entering entrepreneurial firms (see, e.g., Davila and Foster, 2007). Rather than taking an ex post view of control instituted by outside investors, we argue that debt can send a valuable signal to prospective investors that such governance is already in place. In this sense, lender presence can help investors to assess arm's length equity transactions due to their early screening and the effective governance that they institute.

Figure 1 illustrates the main characteristics of our framework. Once an entrepreneurial project is transformed into an early stage firm, in the absence of external financing and control, the potentially conflicting logics between entrepreneurs and investors arise from the discretionary use of cash flows in the pursuit of private benefits (Kochhar, 1996), and an overall less professional management (Bloom et al., 2012). By imposing a market type governance (David et al., 2008; Williamson, 1988), debt raises accountability to external constituents and enacts a mechanism of monitoring and control of firm cash flows and more generally firm operations (Jensen, 1986; Kochhar, 1996). Failure to adhere to debt related

obligations can lead to outcomes as dire as losing the control of the firm (Grossman and Hart, 1982); from an entrepreneur perspective, the risk of this extreme outcome can serve as a powerful disciplining mechanism. Taking all arguments together, we conjecture that given the governance it imposes, debt can serve to mitigate the severe information asymmetry at the early stages of the firm by sending valuable signals to prospective investors.

Hypothesis 1: At the early stages of the firm, debt is positively related to outside equity injections.

1.2.3 The signaling value of debt types

Our baseline hypothesis can be more pronounced depending on the type of debt. The heterogeneity in debt types and their relationship to firm outcomes has received some attention in the case of incumbent firms, but this has been less so for the more opaque start-ups. Even for incumbent firms, the evidence is rather new; for instance, Rauh and Sufi (2010) and Colla et al. (2013) show that debt heterogeneity matters for capital structure, and more generally for firm outcomes. For small firms, but not necessarily start-ups, Hall et al. (2004) and Watson and Wilson (2002) emphasize the importance of screening processes and monitoring costs that may differ between debt types. Robb and Robinson (2014) are likely the first to extensively describe the different typologies of debt for start-ups in the US. They show that bank debt is by and large the most important financing source for start-ups, while Cole and Sokolyk (2018) indicate that 76% of firms use some type of credit instrument at inception and argue that business and personal debt are fundamentally different.

The personal versus business debt distinction is relevant to our study in more than one way. On the one hand, lenders assess personal debt by analyzing the creditworthiness of an individual and not necessarily the viability of the firm's prospects. In many cases, lenders may not know that the loan will be transferred to the funding of a start-up. On the other hand, business debt is subject to greater scrutiny at contracting stages and more intensive monitoring and control ex post (Cole and Sokolyk, 2018). Since outside investors are less interested in the owner's creditworthiness, but more so in the screening of firm prospects and the governance that a successful loan granting imposes, business debt encompasses more valuable informational attributes. In essence, the arguments for our baseline hypothesis, become stronger in the case of business debt. By imposing a stronger monitoring of firm activity, business debt can act as a fundamental governance mechanism to deter discretionary behaviors (Park 2000). Conversely, the willingness of the entrepreneur to take risk and use

personal debt in the early stage firm does not signal the existence of governance or higher accountability—high personal debt can provide discretion in management and be detrimental to an effective governance role of debt—but instead can signal commitment to the firm. While early signaling studies have looked at entrepreneur ownership (Downes and Heinkel, 1982), the unlimited liability of personal debt brings about a commitment component that can enhance the signaling mechanism in the governance role of debt.

Within the types of business debt, bank business debt can further strengthen the signal to outside investors. In a context where hard, quantitative information is scarce, stronger ties to banks can make debt signals more credible as banks usually access soft information on the firm (Agarwal and Hauswald 2010; Degryse and Ongena 2005), which may well serve not only for screening but also for instituting effective control mechanisms (Berger et al., 2017). In this line, David et al. (2008) argue that relational lenders—most common in the case of early stage firms—can help to resolve liquidity concerns and more closely monitor borrowers to obtain soft information that can be used for a more active control of the firm. Overall, banks specialize in monitoring ex post firm behavior not only by imposing tough initial conditions, but also through a strict governance of debt such as a continuous control and potential revocation of credit lines (Acharya et al. 2014). Thus, the bank-firm relationship can serve for mitigating early stage liquidity concerns, and importantly can be a reliable signal to outside investors of an effective governance that guides firm management.

Taking all arguments together, we believe that business debt, and especially bank business debt, sends a stronger signal to outside investors. This is so given that its contracting process is costlier, requires more firm-specific information, and the ex post governance is supervised by specialized lenders. Moreover, the entrepreneur's commitment to the firm can be increased by the presence of personal debt, which although not related to governance mechanisms, can add an additional layer of reliability towards external constituents.

Hypothesis 2a: At the early stages of the firm, business debt, and especially bank business debt, is positively related to outside equity injections.

Hypothesis 2b: At the early stages of the firm, business debt, and especially bank business debt, is more positively related to outside equity injections in the presence of personal debt.

1.2.4 Capital needs and the signaling value of debt

Connelly et al. (2011) explain that the value of a signal can be stronger or weaker depending on firm specific factors, but also on factors related to the signaling environment. Given that information asymmetries and the potentially related problems can vary with the environment, institutions or industry are potential factors that can influence the usefulness and reliability of a signal. We focus on the role of the industry in strengthening the value of the debt signal, as firm capital structure can be related to industry characteristics (MacKay and Phillips 2005; Myers 1984; Scherr et al. 1993). To the extent that debt financing is more relevant in certain industries, we would expect an industry heterogeneity in the signaling value of debt for outside investors.

The contracting and use of debt has been shown to have more importance in capital intensive industries (Jordan et al. 1998), which poses a natural industry classification for the heterogeneity in the signaling value of debt. Indeed, Titman and Wessels (1988) and Rajan and Zingales (1995) argue that the reliance on debt financing is key for firms that feature high levels of tangible assets, a common aspect in high capital intensive industries. Drawing on these arguments, there are some connected features that affect early stage firms within our theoretical framework. On the one hand, the governance role of debt described in hypothesis 1 and Figure 1 can be more straightforwardly implemented in capital intensive industries with easier to evaluate tangible assets. In this line, the presence of tangible assets can facilitate the disciplining of discretionary unaligned behavior (Gompers and Lerner, 2002), which can be sanctioned more readily through changes in control (Grossman and Hart, 1982). On the other hand, in high as compared to low capital intensive industries, having contracted debt is key for achieving growth, one of the main objectives of early stage firms (Carpenter and Petersen 2002). Specifically, to achieve growth, early stage firms in high capital intensive industries need to expand their operations by increasing their tangible asset base. This presupposes a more difficult to scale up business model in the absence of available and well governed financing, which debt can ensure (Gompers and Lerner, 2002).

Thus, although the governance role of debt can be facilitated by the attributes of firms in capital intensive industries, its existence is important for potential investors as it more effectively safeguards the adherence to contractual obligations and a less discretionary management of the entrepreneurial firm. We believe that, although the environment represents a relatively underresearched topic within signaling theory (Connelly et al., 2011), industry

heterogeneity in capital requirements adds an important layer to the relationship between early stage debt and outside equity.

Hypothesis 3: At the early stages of the firm, debt is more positively related to higher outside equity injections in high (relative to low) capital intensive industries.

1.3 Data and sample

We conduct our study using the Kauffman Firm Survey (KFS), which provides information on start-ups founded in 2004 as new independent businesses and are representative of the US population. The survey tracks 4,928 start-ups from their inception and through seven follow-up years, and provides information on industry, location, employment, credit scores, financials, as well as detailed demographics of the entrepreneurs. All firms were sampled in their founding year, thus avoiding left-censoring problems.[2]

The firm's legal form is a key feature for potential outside equity injections. The KFS includes sole proprietorships, limited liability companies (LLC), corporations and partnerships.[3] We discard sole proprietorships and partnerships. First, sole proprietorships are unincorporated businesses owned by an individual and do not distinguish between the business and the owner personal income or wealth filings. By definition, there are no outside investors in sole proprietorships. Second, we also exclude partnerships, a specific type of business in which an agreement establishes key corporate decisions (e.g. on profits or ownership). Especially at early stages, these particular conditions can distort arm's length private equity transactions that are within the focus of our study (also, only 42 firm-year observations are partnerships that receive outside investment).

Our final sample consists of 5,619 firm-year observations corresponding to 833 start-ups in year 2004. Table 1.1 summarizes the variables, while Appendix Table 1.A1 provides their detailed definitions; correlations are presented in Table 1.A2.[4] For instance, the average levels of debt and outside equity are $302,364 and $98,222, respectively. In line with previous

[2] The sampling process started from a Dun & Bradstreet database containing 250,000 businesses that had started operations in 2004 from which a random sample of 32,469 was drawn, and 4,928 responses were recorded in the baseline survey. Dun & Bradstreet provides information on more than 225 million businesses worldwide. For the final sample, businesses were excluded if they had an EIN, had scheduled C income, or had paid taxes prior to 2004 (Robb and Robinson, 2014).

[3] Corporations in the KFS include two subcategories: C-corporations (the traditional business that is held legally liable for the actions and debt of the business) and the subchapter S-Corporation (a special type of corporation that, for instance, allows for profits and losses to be passed through shareholders' personal tax filing).

[4] We do not use ratio measures to avoid that accounting rules mechanically and jointly drive debt and outside equity.

literature (e.g. Puri and Zarutskie, 2012), outside equity is concentrated in a small proportion of start-ups (at the 90th percentile, the value for this variable is 0).[5]

Several control variables are related to financial and owner characteristics, and the business form (LLC or corporation type). The median start-up has revenues of $140,000, two employees, profits of $3,500, and a ROA (profit divided by total assets) of 3.5%. Main owner characteristics indicate that the median entrepreneur is 47 years old, has been working in the industry for about 12 years and, whereas the median entrepreneur did not set up a business, many did. Most entrepreneurs are males (78%) and 88% are born in the US.

1.4 Empirical strategy

Most start-ups do not raise outside equity either because they are not able to attract investors or because they are not interested in the funds and presence of external investors. These are two different mechanisms that generate zeros in the outside equity variable.[6] Selection models are especially useful in this context. Outside equity investments are a two-stage process in which first the start-up either receives or not outside equity, and second, conditional upon receiving outside equity, the amount is set. In our case, the second "amount equation" is not strictly random or independent of the first "participation equation" (e.g. firms with certain levels of revenues and traction may be more prone to raise private funds). Therefore, we use the Heckman selection model, which allows for dependence between the two equations and corrects for it when computing the standard errors. The selection (1.1) and outcome (1.2) equations are:

$$Out\_E\_Dum_{i,t} = \alpha + \beta_1 Ln(Debt)_{i,t} + \beta_2 Out\_E\_Dum_{i,t-1} + \beta_3 X_{i,t} + \beta_4 Z_{i,t} + \delta_t + \gamma_l + \varepsilon_{i,t} \quad (1.1)$$

$$Ln(Out\_E)_{i,t} = \alpha + \beta_1 Ln(Debt)_{i,t} + \beta_2 X_{i,t} + \beta_3 Z_{i,t} + \delta_t + \gamma_l + \lambda_{it} + \varepsilon_{i,t} \quad (1.2)$$

[5] One related concern could be the presence of convertible debt, which is not given any treatment or importance by Robb and Robinson (2014) and KFS reports. First, if convertible debt were to drive our results, we should find a negative and significant relationship between debt and equity. This would make it more difficult for our estimates to report a positive association between debt and outside equity, and makes our results conservative. Second, we proxy for the existence of convertible debt at the firm-year level by combining KFS questions "F2a. How much of Owner X own money did he/she put into the business during the current calendar year?" and "F2b. What percentage of the business did Owner X own on December 31 of the current calendar year?". The logic is that, if Owner X does not put any money in the business in the current calendar year, but his/her percentage of ownership increases, there is a strong indication of a convertible debt instrument. We identify 50 firm-year observations that take the value of one according to the criteria above. When removing these observations from our analyses, or when controlling for this variable, we obtain similar results.

[6] We do not use Tobit regressions, since these assume that the same probability mechanism generates both the zeros and the positive values (Cameron and Trivedi 2005), which is not true in our context.

where $Out\_E\_Dum_{i,t}$ is a binary variable that takes the value of one if firm *i* receives outside equity financing at time *t*, and $Ln(Debt)_{i,t}$ and $Ln(Out\_E)_{i,t}$ are the natural logarithms of one plus the amount of debt and outside equity, respectively, that firm *i* acquires at time *t*. $X_{i,t}$ and $Z_{i,t}$ include firm and owner characteristics, respectively (see Table 1.1). We also control for year (δ_t), industry (γ_i) and location (λ_{it}) fixed effects. Finally, $Out\_E\_Dum_{i,t-1}$ is a binary variable that takes the value of one if firm *i* received outside financing in *t-1*, and zero otherwise. This variable fulfills the exclusion restriction; thus, it is included only in the selection equation. We assume that the lagged value of $Out\_E\_Dum_{i,t}$ is significant in the selection equation (probability of being invested) but not in the amount equation (having received outside equity does not drive the amount to invest, which will most probably differ across firms).

We use the Heckman model to determine the main relationships between the variables of interest, and include a comprehensive set of control variables to address potential omitted variable problems. However, debt and outside equity could still be subject to simultaneous causality. In Section 2, we have theoretically analyzed this aspect, and argued for the direction of the signal from debt to equity. To empirically address this concern, we design a propensity score matching and further tackle endogeneity through an instrumental variable approach.

We additionally use propensity score matching (PSM) to match two groups of start-ups with similar characteristics at inception (year 2004) that differ in the level of debt. Matching at inception is an important feature since we are also interested in the use of debt, not only its existence. We obtain two groups: the treated (high debt) and the control (low debt) groups. The PSM uses the predicted values from a logit regression to estimate the propensity score:

$$P(Debt\_Dum_i \mid X_i) = F(\alpha + \beta_1 Ln(Out\_E)_i + \beta_2 Controls_i) \qquad (1.3)$$

where $Debt\_Dum_i$ takes the value of one if the start-up has high debt in 2004 (i.e. top quartile of the debt variable distribution) and zero if the firm has low debt in 2004 (i.e. lower two quartiles). F(.) is the logistic function that includes predictor variables: $Ln(Out\_E)_i$, the natural logarithm of outside equity plus one, and a series of firm and owner characteristics.

We match each high debt start-up with one control firm using closest neighbor matching without replacement and requiring exact matching by industry (NAICS 2-digit).[7] This process successfully matches 368 firms (184 in each group), statistically similar on the selected

[7] As suggested in Guo and Fraser (2014), we use a caliper width of 0.25*standard deviation of the propensity score variable (i.e. 37,900). Observing that this width does not successfully match all variables (e.g. t-tests between groups for some of the matched variables remain significant at 10%), we progressively reduce the caliper until all matching variables are not significantly different between the two groups (i.e. we finally use a caliper width of 15,000).

characteristics. The matching variables are selected using the following criteria. First, we match by size, since high debt firms may be larger than low debt firms and investors would not be attracted by the debt signal itself but by size. To avoid this confounding argument, we include ln(Revenues), ln(Total assets) and number of employees in our matching procedure. Second, we use ROA as a profitability variable as it could be that financial institutions grant more loans to more profitable firms, which also attract more outside equity. Third, risk is a crucial factor for both debt and equity; we mitigate this confounding effect by including credit risk as a matching variable. Fourth, we match by the initial level of outside equity, as our PSM strategy is designed to observe differences in outside equity injections over time. Fifth, since we also analyze the role of debt usage (i.e. asset structure), we match by those variables that show significant explanatory power in our regressions analyzing outside equity injections (i.e. Heckman model in Table 1.2): ln(Cash) and ln(Inventory).

Finally, we include owner characteristics. To choose among the different variables, we regress the outside equity dummy (having received outside equity) on each of the owner characteristics variables and four additional models including all owner characteristics variables and, sequentially and jointly, industry, year and state fixed effects (see Appendix Table 1.A3). The only variables that consistently show explanatory power for receiving outside equity across all models are week hours dedicated to the business, previous start-up experience and education. This evidence goes beyond the PSM matching, and will be discussed further in the results section.

1.4.1 Exploring industry heterogeneity and real effects

To study industry heterogeneity in the relationship between debt and outside equity (hypothesis 3), and explore firm real effects related to the use of debt, we create two splines for our coefficients of interest for high and low capital intensive industries. We follow the definition of Acemoglu and Guerrieri (2008), which is based on the same NAICS industry classification used in the KFS, to classify firms into high and low capital intensive industries. We run binary and OLS models on the following general specification:

$$Outcome=\alpha+\beta_1 Ln(Debt\_HighCap)_{i,t}+\beta_2 Ln(Debt\_LowCap)_{i,t}+\beta_3 X_{i,t}+\beta_4 Z_{i,t}+\delta_t+\lambda_{it}+\varepsilon_{i,t} \quad (1.4)$$

where *Outcome* is sequentially the outside equity dummy (*Out_E_Dum*), the outside equity positive amount (*Ln(Out_E>0)*), ln(Revenues), market share (the percentage of the firm's revenues in the industry-year) and ROA. The coefficients of interest are β_1 and β_2 which split

the overall coefficient of debt between high and low capital intensive industries. The term $Ln(Debt\_HighCap)_{i,t}$ captures the value of debt when the firm is in a high capital intensive industry and zero otherwise; while $Ln(Debt\_LowCap)_{i,t}$ takes the debt value in low capital industries and zero otherwise. These two terms cover the complete spectrum of industries. We are interested in the statistical and economic comparison of these two coefficients, which reflect whether trends (i.e. positive or negative) and slopes (i.e. magnitudes) are different depending on industry type. We also treat the debt decompositions (i.e. personal, business, bank and non-bank) in a similar fashion by creating industry-type splines for each coefficient of interest. Similar to equations (1) and (2), $X_{i,t}$ includes firm-level characteristics while $Z_{i,t}$ captures owner characteristics. Year and location fixed effects are also included.

1.4.2 Robustness checks: reduced sample and instrumental variable approach

For the period 2009-2011, the KFS survey includes a specific question that distinguishes between start-ups that actively seek outside equity financing and those which do not. This offers a clear rule for excluding the firms that report zero values in the outside equity variable due to not seeking outside equity. The survey only contains this question between 2009 and 2011, and thus we use this analysis as a robustness test. For this sample we can assume that the same probability mechanism generates both zeros (firms which fail to raise outside equity) and positive values (firms which succeed to raise outside equity), and use a Tobit model.

Next, there could still exist factors that confound the ability to raise both debt and outside equity. To reduce such endogeneity concerns, we re-estimate our baseline result using an instrumental variable approach. We use the number of small bank branches per county at the start of our sample (year 2004) as an instrument for debt and the governance signal within. First, in line with Degryse and Ongena (2005), we expect bank proximity to have a negative effect on information asymmetry and facilitate loan granting. Second, lending to start-ups tends to be higher in regions with more small banks (Berger et al. 2015). Third, as relationship lenders, small banks are better suited to ensure a governance role of debt, as they have been shown to have a comparative advantage in using soft information to alleviate the financial constraints of small businesses (Agarwal and Hauswald, 2010; Berger et al., 2017).

Finally, for the instrument to be valid it should satisfy the exclusion restriction. One concern could be that if local economic conditions are related to banking competitiveness, the instrument might also influence the ability of firms to raise outside equity. In this case, the

instrument would be invalid and the coefficients biased. We address this concern by controlling for time-varying state level macroeconomic conditions obtained from the Bureau of Economic Analysis (GDP per capita and personal income growth) and from the Bureau of Labor Statistics (unemployment growth).

1.5 Results

Panel A of Table 1.2 presents the results from incremental specifications for the probability of receiving outside equity (first-stage selection equation of the Heckman model). We consistently find that debt and its decomposition into personal and business debt are positively related to the likelihood of receiving outside equity. The coefficients are largely stable across specifications, even to the inclusion of owner characteristics. As for the latter, untabulated coefficients indicate that week hours dedicated to the business, start-up experience and the level of education are the only owner characteristics that are significant and positively correlated to the likelihood of attracting outside equity. This is in line with Appendix Table 1.A3 that explores the relationship between owner characteristics and receiving outside equity.

The identifying variable (the lagged outside equity dummy) is positive and significant, revealing that having been invested in the previous year has a positive effect on receiving funds in the current period. Results are consistent across specifications. One salient finding is that cash is positively related to the likelihood of receiving funds. This can be one of the information channels for the governance role of debt in early stage firms.

Panel B of Table 1.2 reports the results of the relationship between debt and the magnitude of outside equity injections (second-stage outcome equation). The number of observations is reduced to include start-ups that received outside equity. Results indicate a positive relationship between debt and outside equity (columns 1, 3 and 5), supporting our hypothesis 1. Next, we show that this main effect is mostly driven by business debt, while personal debt has an insignificant link to outside equity (columns 2, 4 and 6). To explore hypothesis 2a in detail, we decompose business debt into bank and non-bank business debt (the latter includes family, employee or government credit). The results in columns (7) and (8) show that, among the two types of business debt, bank business debt is significantly and positively associated to outside equity injections, further supporting our hypothesis 2a. In addition, the unreported owner characteristics do not show any significant association with the

amount of equity raised. This indicates that owner characteristics may be important determinants for the decision to invest, but not for the amount invested.

To test hypothesis 2b, we replicate the Heckman model by decomposing the business debt and bank business debt coefficients between firms that feature personal debt and those that do not. The results in columns (1-2) and (3-4) of Table 1.3 largely uphold our hypothesis: the positive relationship between business, and especially bank business debt and outside equity injections is stronger in the presence of personal debt. We take a step further and add a governance intensity layer by identifying firms with active bank credit lines, which occurs for 22% of the observations in our sample. As we have argued, banks are able to better ensure an effective governance and control, and one channel that allows them to do so is the active monitoring of credit lines. In columns (5-6) and (7-8) we reveal that having an active credit line significantly enhances the positive link between bank business debt and outside equity, and even more so in the presence of personal debt. For all comparisons in Table 1.3, untabulated t-tests show that the coefficients of interest are significantly larger than their counterparts.

The PSM results also support the above argumentation. We start by corroborating the effectiveness of the matching procedure. Appendix Table 1.A4 summarizes the 184 matched-paired observations in 2004 resulting from the PSM, as well as the overall sample in the same period. T-tests confirm that the matching process is successful as there are no significant differences in any variable across groups, meaning that each paired observation is equal in all matched dimensions. Table 1.A4 also reports descriptive statistics for the 2004 sample. Importantly, the matching results go beyond the selected variables. For instance, other owner characteristics are also similar between the matched samples even if not included in the matching (e.g. owner age or industry experience).

Panels A of Figure 2 and Table 1.4 illustrate debt levels over time for the two matched groups. After matching in 2004, start-ups first show a certain path dependency, followed by a converging trend until the financial crisis, when firms seem to stabilize their level of debt. We are mainly interested in the amount of outside equity that the two types of firms are able to attract. Panels B of Figure 2 and Table 1.4 reveal that outside equity injections are significantly different between high and low debt firms in financial distress times (years 2007 and 2008). This result upholds hypothesis 1 especially for periods in which capital providers are constrained, and the debt signal could hold higher value.

Two factors can drive our PSM results. First, acquiring debt at inception signals stronger governance mechanisms right from the beginning of firm operations (e.g. lower

discretionary management) and also a lender-firm relationship that could favor future credit availability. These aspects can be especially valuable for outside investors in crisis periods. Second, the use of debt through investments that start-ups make in 2005 and 2006, the years prior to the observed significant difference in outside equity, can serve as information channels. Table 1.5 reveals that high debt start-ups show higher values for balance sheet asset items, with more significant differences two years after debt contracting. Accordingly, firms that acquire more debt at inception have higher levels of cash, inventory and fixed assets, suggesting that debt is not only contracted but also used. These findings provide support to the Heckman analysis, especially to the role of cash as an information channel. For robustness, we redo our PSM analysis by debt category. Matching by business debt, we find that high business debt start-ups attract more outside equity, especially close to crisis years. In contrast, matching by personal debt does not reveal any significant results.

Next, we use our matched groups to explore the real effects of debt usage. We track firm growth (revenues) and profitability (ROA). Panel C of Table 1.4 shows that high debt start-ups achieve greater growth relative to low debt ones in 2009-2010, after the documented outside equity injections. However, growth does not seem to come along with profitability, as ROA is not statistically different across groups (Panel D of Table 1.4). It may be that during the early stages of the firm, profitability is postponed in favor of growth. One important result is that the credit risk of our matched groups does not differ during the whole analyzed period (Panel E of Table 1.4). This measure, that can also be a proxy of firm quality, is less endogenous as it employs ratings from an exogenous source, Dun & Bradstreet. Over the entire period, firms in the high and low debt groups appear to be equally able to contract additional financing; this strengthens our signaling interpretation.

1.5.1 Industry heterogeneity and real effects

Table 1.6 reports the results for hypothesis 3 by splitting the coefficients of total debt and its decompositions into the trends corresponding to high versus low capital intensive industries. Columns (1) to (3) show that the probabilities of attracting outside equity are positive for all debt types across industries. However, t-tests show that the coefficients for total, business and bank business debt are larger in high as compared to low capital intensive industries.

The results on the trends between debt and the magnitude of outside equity injections reveal a clear cut heterogeneity in the differential effects by industry, supporting our hypothesis 3. We systematically find that the magnitude of the association between debt and

outside equity injections is about two times larger in high with respect to low capital intensive industries (column 4 in Table 1.6). This differentially larger effect is also found for business debt (column 5) and bank business debt (column 6). Indicatively, in high capital intensive industries, a one standard deviation increase in debt is associated to a 4.3% increase in outside equity with respect to the average level. For reference, across industries, a one standard deviation increase in debt is associated to a 2.4% increase in outside equity with respect to the average level (column 5, Panel B of Table 1.2). Throughout, t-tests confirm that debt coefficients are significantly larger in high as compared to low capital intensive industries.

Next, we analyze the link between debt types and firm economic outcomes. First, in line with the PSM results, we find an overall positive relationship between debt and revenues (column 1 in Table 1.7). Exploring the heterogeneity in this result, we find that this positive effect is mainly driven by business debt (column 3 in Table 1.7) and is significantly and economically larger for firms operating in high capital intensive industries (column 4 in Table 1.7). Second, we analyze the real effects of debt types on market share (the percentage of firm's revenues in industry-year, with a mean value of 0.89 and a standard deviation of 4.33). While there is no overall effect of debt (column 5), there is a strong positive association between debt and market share in high capital intensive industries (column 6). Decomposing, there is a positive association between business debt and market share (column 7), which becomes statistically and economically stronger in high capital intensive industries (column 8). Third, we show that at early stages, these effects of debt related to firm growth, do not materialize in higher profitability: ROA results (columns 9 to 12) show no significant relationship between debt and profitability for any debt decomposition across industry types. These results corroborate our PSM analysis and reveal important heterogeneous real effects by industry type.

1.5.2 Robustness: results from reduced sample and instrumental variable approach

First, for 106 observations during 2009-2011, the KFS allows us to identify precisely the firms that actively seek outside equity investments and were successful or failed in the process. For this subsample we run Tobit regressions. In untabulated regressions, we find strong results for the positive relationship between business debt and outside equity injections.

Second, we further tackle endogeneity concerns by replicating our baseline results for the relationship between debt and outside equity using an instrumental variable approach. In

Table 1.8, we use the number of small bank branches in each county at the start of our sample (year 2004) as an instrument for debt and its governance role. Similar to Berger et al. (2017), we define small banks as those with total assets below $1 billion.[8] The complete specifications include the full set of firm and owner characteristics, as well as time-varying macroeconomic conditions, and year and industry effects.

The first stage results (columns 1 and 3 in Table 1.8) confirm the positive and significant relationship between the instrument and debt. This is in line with the idea that bank proximity can help to decrease information asymmetry (Degryse and Ongena 2005), and that small banks are especially suited to use soft information to screen and control early stage firms (Berger et al., 2017). The second stage results (columns 2 and 4 in Table 1.8) reveal that the instrumented level of debt is positively and significantly related to outside equity financing. Overall, the hypothesized relationship between debt and outside equity is corroborated by further addressing potential endogeneity concerns.

1.5.3 Ruling out alternative explanations based on the pecking order theory

One concern is whether our results follow a pecking order, in which firms with high debt turn to the last available financing source, outside equity. In our theoretical framework, and in line with Robb and Robinson (2014), we have argued that such theories may apply better to incumbents than to start-ups. Here we address this issue empirically. We first analyze the rate of approval or denial of debt applications, which KFS reports for the 2007-2011 period, for high relative to low debt firms. We categorize firms into high and low debt groups in year 2004 using the same procedure defined in the PSM analysis. High (low) debt firms made 367 (346) debt applications, being approved in 77% (66%) of the occasions. Thus, high debt firms do not seem to shift towards outside equity due to their impossibility to raise debt financing.

One may however argue that the high debt firms that apply for debt financing may be a selected sample of firms that anticipate success in the application process. To address this concern, we use the KFS question (available for years 2007-2011): “F14g. During this year, was there any time when the business needed credit but did not apply because you thought the application would be denied?”. We create a dummy variable that takes the value of one for firms that did not apply due to anticipating rejection, and zero otherwise. In the high debt group, 18% of firm-year responses indicate not applying for debt financing because they expected a denial. In the low debt group, 16% answered in the same manner. This difference

[8] For robustness, we define small banks as those with total assets below the median, and obtain similar results.

is not statistically significant in any period, suggesting that there is no systematic difference in the anticipation of debt application denials between the high and low debt groups.

Finally, another concern would be that high debt firms might have worse credit scores and therefore the only financing option they are left with is outside equity. Our PSM results show that both the high and low debt groups have similar credit risk (Panel E of Table 1.4); that is, even with similar levels of credit risk over the entire panel, high debt firms are more likely to attract outside equity investors. In addition, we include credit risk as control variable in all regressions. Overall, while the pecking order theory may be more useful for incumbent firms, we believe that our signaling framework is more suitable to the start-up context.

1.6 Discussion and contributions

1.6.1 Contributions to theory

We push a step further the literature on the relevance of start-ups' characteristics for financing options. The baseline premise in our theoretical framework is that early stage firms are opaque and signals based on their key attributes can help investors in their decisions. Our theoretical arguments develop a governance understanding of debt that can serve to mitigate information asymmetries related to the management and control of the young firm. Building on seminal governance studies in economics (Jensen, 1986) and management (Kochhar, 1996), we posit that the problem of discretionary control of the firm is exacerbated in the entrepreneurial firm. We propose that by commanding greater accountability to external constituents, outside investors can interpret the presence of early stage debt as a valuable signal of a market like governance (David et al., 2008; Williamson, 1988).

Our work serves to reconcile some of the perspectives on the lender versus investor information interpretation processes. Lenders tend to focus their governance mechanisms on the downside risk, linked to which investors could evaluate their position as residual claimants (Grossman and Hart, 1982; Jensen 1986); however, investors have been shown to select firms mostly based on their upside growth potential (Gompers and Lerner, 2002). As we have argued, the lender perspective can bring value to the information interpretation process of investors. While Ueda (2004) proposed that investors can have informational advantages, in recent evidence Berger et al. (2017) have shown that specialized lenders are most suited to alleviate the financing constraints of entrepreneurial firms by relying on relationship lending and soft information. We highlight that in the case of young firms, a

lender focus could provide informational benefits to investors. As such, business debt requires competitive screening and adhering to tight monitoring standards which taken together presuppose a costly and difficult to imitate process. Foremost, by using early stage soft information, lenders are able to guide the prevalent discretionary, less professional management of young firms (Bloom et al., 2012) towards a more market oriented one (David et al., 2008; Williamson, 1988), which investors can evaluate as a positive mechanism for future growth prospects.

By theoretically analyzing the intensity of the debt governance signals at firm and industry levels, our framework contributes to expanding the knowledge on signaling rationales in entrepreneur-investor relationship, which have ranged from signaling in IPOs (Arthurs et al., 2009; Pollock and Gulati, 2007) to the importance of human capital (Ahlers et al., 2015; Davila et al., 2003) and competitive financing (Islam et al., 2018). Our work also helps to integrate existing knowledge on the joint usefulness of firm financial information (Armstrong et al., 2006; Hand, 2005) and non-financial attributes such as ownership characteristics (Baum and Silverman, 2004; Bernstein et al., 2017; Dimov and Shepherd, 2005; Maxwell et al., 2011) to analyze the unique phenomena of entrepreneur-investor relationship (e.g. Arthurs et al., 2009; Cassar, 2004; Cassar et al., 2015). Throughout, our framework shows that some of the mainstream insights for incumbent firms may not prevail for early stage firms, thus revealing important boundaries of existing theories. For instance, the use of early stage signals of firm governance may supersede the assumptions on the ordering of financing sources in incumbent firms.

1.6.2 Contributions to empirics and practice

Our theoretical and empirical analyses together support that, given debt's ubiquitous presence at the early stages of the firm, investors can mitigate the high informational risk in the start-ups' context by relying on lenders' incentives and ability to monitor firm activity. The various layers of heterogeneity in our results lead to implications for both firms and investors.

The governance signal is enhanced in the case of business debt, which entails costlier screening process and imposes a tougher monitoring that restricts discretionary firm management under the dire penalty of losing control rights. The effective governance of business debt engenders a greater external accountability of entrepreneurs, which is intensified in the presence of personal debt. Although personal debt is less related to such governance mechanisms, its presence can signal the entrepreneur's commitment with the firm.

There are thus two-sided advantages from contracting business debt: the firm benefits not only from lifting roadblocks to growth, but also from a solid anchoring point for prospective investors. These advantages are stronger in capital intensive industries, which feature higher reliance on financing and more difficult to scale up business models.

The signaling effect is more salient in crisis times, when constrained capital providers may value more an effective governance of debt. This finding extends the existing evidence on crisis effects in the development stages of the firm (Block and Sandner 2009), by suggesting that the liquidity provided by debt jointly with an increased accountability of the firm towards external constituents can link to attracting outside equity in crisis times. Such accountability effects can be enhanced by early stage bank-firm relationships, particularly in capital intensive industries, in which bank business debt has a significantly larger effect on outside equity injections. Transmitting information through the bank-firm relationship can be based on the advantages of specialized lenders in using soft information and their greater ability to actively monitor credit lines (Berger et al., 2017; Degryse and Ongena, 2005).

It is not only the mere existence of debt that strengthens the signal, but also the use of debt. Our analysis reveals that for the first years of activity, high debt firms can transmit information to investors through balance sheet items such as fixed assets or cash holdings that can lead to sustained firm activity and valuation (Hand, 2005). These findings contribute to the complementarity of different types of information that can help to explain investor decision-making. Whereas owner characteristics such as previous start-up experience, time dedicated to the business and education can be related to attracting outside equity, ceteris paribus, there is an important relevance of debt types for attracting outside equity as well as for the magnitude of injections.

Next, we go beyond the signaling role of debt to reveal firm real effects. Overall, we do not find effects on profitability, but reveal important differential growth effects: debt, and especially business debt is positively associated with revenues and market share, and even more so in capital intensive industries. This is in line with the idea that start-ups mainly focus on growth as value enhancing (Carpenter and Petersen, 2002) or as a strategy towards going public (Puri and Zarutskie, 2012). For instance, Choi et al. (2016) show that the governance role of debt fosters innovation, a potential channel for growth. An underlying mechanism is that the governance role of debt directs entrepreneurs to more market oriented management practices (Bloom et al., 2012), which are congruent with the preferences of outside investors and the more formal control systems that investors tend to impose (Davila and Foster, 2007).

Our findings contribute to core policy debates on economic growth.[9] Understanding the underpinnings of the governance role of debt for outside equity investments and firm real effects paves the way for policy-making that can range from relaxing the regulation of platforms of venture lending and investment, to reforming economic programs for credit promotion to young firms. For the latter, regulators could consider the extent to which credit programs are suitable. Our results show that in capital intensive industries, there is a higher signaling value of debt. In these cases, the capital market may function better with fewer interventions, as equity providers can more readily use firm and entrepreneur level signals. Conversely, in emerging industry contexts, financing grants can hold a stronger signaling value for attracting outside equity (Islam et al., 2018). If the emerging industries are also less capital intensive, regulators could strategically consider interventions, for instance by designing financing programs.

1.6.3 Limitations and extensions

To conclude, we point to some limitations of our study. While our work explores various layers of heterogeneity, it has some limitations that can serve as a stepping stone. Future research could attempt to employ quasi-natural experiments to more narrowly identify the underpinnings of the causal mechanisms between debt and outside equity. These, however, are not always available. A long-standing unresolved issue relates to the extent to which new firms can be leveraged, or how more sophisticated hybrid financial instruments such as convertible or preferred stock should be employed. In this study we do not indicate an optimum amount of debt that a start-up should contract; this issue could be tackled through formal models from the more traditional capital structure literature, such as the static trade-off theory. In informationally opaque contexts, these models may benefit from integrating the role of incentives on performance at the time of changes in capital structure (Kaplan 1989). Finally, there is an increasing trend to study debt concentration (Colla et al., 2013; Rauh and Sufi, 2010). Whereas debt concentration is a characteristic usually found in established firms, the potential implications for young firms remain underexplored. All in all, future research could use our study as a step toward bridging the gap between the research on start-ups and incumbent firms.

[9] See for example the European Angels Fund initiative (http://www.eif.org/what_we_do/equity/eaf/index.htm) where European institutions co-invest with business angels or the Kauffman Foundation letter to the US Senate expressing the need to promote equity investments at early stages of the firm (http://www.kauffman.org/~/media/kauffman_org/resources/2016/kauffman_foundation_senate_finance_tax_reform_working_group_letter_4_15_15.pdf).

Table 1.1. Descriptive statistics of main variables

	Obs.	Mean	Std. dev.	p50	p90
Main variables					
Ln(Debt)	5,619	8.598	4.656	10.309	12.612
Ln(Personal debt)	5,619	4.333	5.000	0	11.082
Ln(Business debt)	5,619	3.614	5.090	0	11.482
Ln(Bank business debt)	5,619	2.974	4.686	0	10.820
Ln(Non-bank business debt)	5,619	0.640	2.458	0	0
Ln(Out_E)	5,619	0.710	2.861	0	0
Out_E_Dum	5,619	0.060	0.238	0	0
Control variables					
Crisis	5,619	0.243	0.429	0	1
Firm characteristics					
Ln(Revenues)	5,619	10.314	4.757	11.849	14.403
Profits (K$)	5,619	-61.104	4,808.841	3.500	150.000
Credrisk	5,619	2.931	0.980	3	4
Employees	5,619	5.940	17.373	2	13
Hightech	5,619	0.168	0.374	0	1
Ln(Cash)	5,619	8.183	3.670	9.210	11.562
Ln(Accounts receivable)	5,619	6.473	5.171	8.517	12.128
Ln(Inventory)	5,619	4.254	5.094	0	11.488
Ln(Fixed assets)	5,619	8.618	4.484	9.913	12.910
ROA	5,619	-9.777	1,153.882	0.035	1.109
Owner characteristics					
Owner age	5,619	47.127	10.647	47	61
Years of industry experience	5,619	13.319	10.539	12	30
Week hours	5,619	44.509	21.229	50	70
Start-up experience	5,619	0.968	1.347	0	3
Education	5,619	6.687	2.026	7	9
Male	5,619	0.783	0.412	1	1
US born	5,619	0.881	0.324	1	1

This table presents the descriptive statistics for the analyzed sample spanning 2004-2011. Out of the total 5,619 observations 2,619 are LLC, 2,234 are S-Corporations, and 766 are C-Corporations. Complete definitions for all variables are provided in Table 1.A1. The high ROA mean and a standard deviation are driven by the presence of five observations. Removing these observations from the sample yields a mean ROA of 0.035 with a standard deviation of 6.107, and a median of 0.035. Running the analysis with this reduced sample does not statistically or economically change our results.

Table 1.2. Panel A. Heckman selection model: First-stage Probit regressions

Dep. var.: Out_E_Dum	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Debt)	0.034***		0.033***		0.032***			
	(0.010)		(0.011)		(0.010)			
Ln(Personal debt)		0.029***		0.036***		0.035***	0.036***	0.035***
		(0.007)		(0.008)		(0.008)	(0.008)	(0.008)
Ln(Business debt)		0.025***		0.025***		0.024***		
		(0.007)		(0.007)		(0.007)		
Ln(Bank Business debt)							0.017**	0.018**
							(0.008)	(0.008)
Ln(Non-bank Business debt)							0.046***	0.041***
							(0.011)	(0.011)
Out_E_Dum $_{(t-1)}$	1.435***	1.410***	1.135***	1.101***	1.064***	1.027***	1.090***	1.021***
	(0.116)	(0.117)	(0.119)	(0.120)	(0.116)	(0.117)	(0.121)	(0.117)
Crisis	-0.132*	-0.146*	-0.321***	-0.338***	-0.290**	-0.312**	-0.331***	-0.307**
	(0.074)	(0.075)	(0.124)	(0.126)	(0.125)	(0.126)	(0.126)	(0.127)
Credrisk	0.027	0.008	0.028	0.011	0.022	0.006	0.012	0.006
	(0.038)	(0.037)	(0.041)	(0.040)	(0.041)	(0.041)	(0.040)	(0.041)
Ln(Revenues)	-0.031***	-0.032***	-0.025***	-0.025***	-0.029***	-0.029***	-0.025***	-0.029***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
Employees	0.003*	0.003*	0.002	0.002	0.001	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hightech	0.210**	0.234**	0.200*	0.195*	0.182*	0.171	0.192*	0.168
	(0.090)	(0.091)	(0.106)	(0.108)	(0.109)	(0.110)	(0.107)	(0.109)
Financial information								
Ln(Cash)			0.040***	0.050***	0.032**	0.041***	0.049***	0.041***
			(0.014)	(0.015)	(0.013)	(0.014)	(0.015)	(0.014)
Ln(Accounts receivable)			-0.008	-0.013	-0.013	-0.017*	-0.012	-0.017*
			(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln(Inventories)			0.011	0.009	0.004	0.003	0.009	0.003
			(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ln(Fixed assets)			-0.004	-0.006	-0.004	-0.005	-0.005	-0.005
			(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ROA			-0.004**	-0.004**	-0.004*	-0.004*	-0.004**	-0.004*
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Profits			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Owner characteristics	No	No	No	No	Yes	Yes	No	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,230	4,230	4,230	4,230	4,230	4,230	4,230	4,230

Panel A of Table 1.2 presents the Heckman selection equation in which the dependent variable is an outside equity indicator that takes the value of 1 if the start-up receives outside equity and 0 otherwise (equation 1). Owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.2. Panel B. Heckman selection model cont.: Second-stage OLS regressions

Dep. var.: Ln(Out_E)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Debt)	0.041		0.052**		0.062**			
	(0.036)		(0.024)		(0.024)			
Ln(Personal debt)		-0.098***		-0.008		-0.002	-0.008	-0.002
		(0.026)		(0.019)		(0.019)	(0.019)	(0.019)
Ln(Business debt)		0.059**		0.045**		0.052**		
		(0.028)		(0.022)		(0.021)		
Ln(Bank business debt)							0.052**	0.061**
							(0.026)	(0.027)
Ln(Non-bank business debt)							0.031	0.039
							(0.029)	(0.028)
Crisis	-0.125	-0.059	0.301	0.150	0.197	0.038	0.146	0.031
	(0.307)	(0.323)	(0.404)	(0.402)	(0.399)	(0.400)	(0.402)	(0.400)
Credrisk	-0.556***	-0.539***	-0.108	-0.139	-0.104	-0.135	-0.140	-0.137
	(0.150)	(0.143)	(0.123)	(0.124)	(0.123)	(0.124)	(0.124)	(0.124)
Ln(Revenues)	0.030	0.031	-0.016	-0.014	-0.022	-0.017	-0.013	-0.015
	(0.028)	(0.027)	(0.027)	(0.026)	(0.029)	(0.028)	(0.026)	(0.028)
Employees	0.040**	0.035**	0.013	0.013	0.014	0.013	0.012	0.012
	(0.017)	(0.018)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Hightech	1.096***	1.085***	0.680**	0.706**	0.878***	0.920***	0.711**	0.935***
	(0.353)	(0.354)	(0.332)	(0.331)	(0.333)	(0.347)	(0.334)	(0.357)
Financial information								
Ln(Cash)			0.236***	0.233***	0.235***	0.231***	0.233***	0.231***
			(0.038)	(0.040)	(0.041)	(0.044)	(0.040)	(0.044)
Ln(Accounts Receivable)			-0.028	-0.032	-0.033	-0.035	-0.033	-0.036
			(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)
Ln(Inventories)			0.047*	0.055*	0.043	0.053*	0.054*	0.053*
			(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Ln(Fixed assets)			0.019	0.021	0.025	0.026	0.021	0.026
			(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)
ROA			-0.012	-0.007	-0.004	0.001	-0.007	0.001
			(0.020)	(0.019)	(0.020)	(0.018)	(0.019)	(0.018)
Profits			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Owner characteristics	No	No	No	No	Yes	Yes	No	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	214	214	214	214	214	214	214

Panel B of Table 1.2 reports the measurement (outcome) equation in which the dependent variable is the logarithm of outside equity (equation 2). Owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.3. Personal debt and credit lines

Dep. Var.:	Out_E_Dum	Ln(Out_E)	Out_E_Dum	Ln(Out_E)	Out_E_Dum	Ln(Out_E)	Out_E_Dum	Ln(Out_E)
Model:	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Personal debt)	0.043***	-0.043	0.034***	-0.024	0.035***	-0.003	0.030***	-0.010
	(0.010)	(0.028)	(0.010)	(0.025)	(0.008)	(0.019)	(0.009)	(0.022)
Ln(Bus debt_Pers)	0.017*	0.093***						
	(0.010)	(0.029)						
Ln(Bus debt_NoPers)	0.034***	0.011						
	(0.010)	(0.027)						
Ln(Bank bus debt_Pers)			0.019*	0.091***				
			(0.011)	(0.034)				
Ln(Bank bus debt_NoPers)			0.016	0.020				
			(0.012)	(0.034)				
Ln(Bank bus debt_CredLine)					0.027***	0.067**		
					(0.009)	(0.032)		
Ln(Bank bus debt_NoCredLine)					-0.002	0.043	-0.001	0.043
					(0.013)	(0.031)	(0.013)	(0.030)
Ln(Bank bus debt_CredLine_Pers)							0.035***	0.082**
							(0.012)	(0.037)
Ln(Bank bus debt_CredLine_NoPers)							0.011	0.044
							(0.014)	(0.048)
Ln(Non-bank business debt)			0.041***	0.039	0.041***	0.037	0.042***	0.039
			(0.011)	(0.029)	(0.011)	(0.028)	(0.011)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	No	Yes	No	Yes	No	Yes	Yes	Yes
Observations	4,230	214	4,230	214	4,230	214	4,230	214

This table reports coefficients of a Heckman two stage model with the first stage indicating whether the firm raises equity financing or not (Out_E_Dum) and the second stage showing the amount raised, Ln(Out_E). We decompose the effects of business debt (columns 1-2) and bank business debt (columns 3-4) into firms that feature personal debt and firms that do not. In columns 5-6, we decompose bank business debt between firms with active credit and those without. Columns 7-8 decompose the coefficient of bank business debt with credit lines between firms with and without personal debt. The included controls and owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.4. Propensity score matching: Differences in means between groups

	2004	2005	2006	2007	2008	2009	2010	2011
Panel A: Debt mean values (see Figure 2)								
Low debt group	4.854	7.059	6.871	7.315	7.149	6.987	6.093	6.595
High debt group	12.042	10.037	9.049	9.846	8.378	9.223	8.564	8.013
t-test p-value	0.000***	0.000***	0.002***	0.001***	0.147	0.013**	0.020**	0.161
Panel B: Outside equity mean values (see Figure 2)								
Low debt group	1.410	1.455	0.666	0.318	0.157	0.311	0.164	0.331
High debt group	1.656	1.213	0.843	1.224	0.880	0.433	0.177	0.187
t-test p-value	0.559	0.599	0.630	0.026**	0.041**	0.716	0.958	0.627
Panel C: Ln(Revenues) mean values								
Low debt group	7.931	9.496	9.495	10.483	9.894	10.706	10.510	11.396
High debt group	8.175	9.243	9.621	10.331	10.425	11.839	11.639	11.780
t-test p-value	0.652	0.688	0.852	0.821	0.490	0.059*	0.087*	0.521
Panel D: ROA mean values								
Low debt group	-0.341	-0.323	0.002	-1.043	-0.942	0.322	1.382	-2.390
High debt group	-0.658	-0.359	-0.303	0.538	-0.368	-0.467	0.197	0.395
t-test p-value	0.350	0.932	0.597	0.149	0.599	0.351	0.441	0.133
Panel E: Credit risk mean values								
Low debt group	3.245	3.098	2.762	2.674	2.663	2.714	2.632	2.845
High debt group	3.277	3.095	2.842	2.634	2.600	2.704	2.875	2.986
t-test p-value	0.664	0.980	0.522	0.782	0.675	0.953	0.176	0.520

This table reports mean differences between the 184 treatment firms (high debt in 2004) and the matched 184 control firms (low debt in 2004). The first two panels report mean differences for debt (Panel A, see also Figure 2) and outside equity (Panel B, see also Figure 2). We also report the evolution of different economic outcomes for the high and low debt groups: Ln(Revenues) as a measure of firm growth (Panel C), ROA as a measure of profitability (Panel D) and firm credit risk (Panel E). Table 1.A1 defines all variables. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.5. Asset decomposition (years 2005 and 2006)

	Mean values in 2005				t-test p-value
	Low debt	Std. dev.	High debt	Std. dev.	
Ln(Cash)	8.084	0.340	8.296	0.271	0.624
Ln(Accounts receivable)	5.210	0.454	5.906	0.412	0.256
Ln(Inventories)	3.767	0.433	4.236	0.408	0.431
Ln(Fixed assets)	8.298	0.392	9.223	0.370	0.087*
	Mean values in 2006				t-test p-value
	Low debt	Std. dev.	High debt	Std. dev.	
Ln(Cash)	7.503	0.392	8.441	0.307	0.058*
Ln(Accounts receivable)	6.284	0.494	6.116	0.430	0.797
Ln(Inventories)	3.550	0.450	4.773	0.451	0.057*
Ln(Fixed assets)	7.890	0.448	9.466	0.371	0.007***

This table reports differences in the asset structure for the two matched groups of start-ups (i.e. high and low debt) for the two years prior to the significant difference in the attraction of outside equity between high and low debt groups. Table 1.A1 defines all variables. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.6. Heterogeneous effects: High versus low capital intensive industries

Dep. var.:	Out_E_Dum	Out_E_Dum	Out_E_Dum	Ln(Out_E>0)	Ln(Out_E>0)	Ln(Out_E>0)
Model:	Probit	Probit	Probit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Debt_HighCap)	0.041***			0.106***		
	(0.012)			(0.029)		
Ln(Debt_LowCap)	0.029***			0.057**		
	(0.011)			(0.026)		
Ln(Bus debt_HighCap)		0.041***			0.092***	
		(0.012)			(0.026)	
Ln(Bus debt_LowCap)		0.018*			0.044*	
		(0.010)			(0.023)	
Ln(Pers debt_HighCap)		0.029**			-0.006	
		(0.011)			(0.027)	
Ln(Pers debt_LowCap)		0.038***			-0.003	
		(0.010)			(0.028)	
Ln(Bank bus debt_HighCap)			0.035***			0.109***
			(0.012)			(0.031)
Ln(Bank bus debt_LowCap)			0.011			0.050*
			(0.010)			(0.025)
Ln(Non-bank bus debt_HighCap)			0.043**			0.056
			(0.019)			(0.038)
Ln(Non-bank bus debt_LowCap)			0.041**			0.040
			(0.016)			(0.031)
Ln(Personal debt)			0.034***			-0.006
			(0.008)			(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Owner characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
β debt HighCap>β debt LowCap	0.077			0.013		
β bus HighCap>β bus LowCap		0.052			0.067	
β bank bus HighCap>β bank bus LowCap			0.038			0.037
Observations	4,008	4,008	4,008	339	339	339

This table presents the heterogeneous effects in the relationship between debt and outside equity (equation 4). We split firms into high and low capital intensive industries and model different debt measures accordingly. Columns 1 to 3 report results of Probit regressions with Out_E_Dum as dependent variable. Columns 4 to 6 report results of OLS regressions with Ln(Out_E>0) as dependent variable. The included controls and owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.7. Real effects: High and low capital intensive industries heterogeneity

Dep. var.:	Ln(Revenues)	Ln(Revenues)	Ln(Revenues)	Ln(Revenues)	Market share	Market share	Market share	Market share	ROA	ROA	ROA	ROA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Debt)	0.053***				-0.006				-0.009			
	(0.013)				(0.012)				(0.023)			
Ln(Debt_HighCap)		0.056***				0.035**				-0.004		
		(0.016)				(0.016)				(0.024)		
Ln(Debt_LowCap)		0.056***				-0.030**				-0.018		
		(0.013)				(0.013)				(0.022)		
Ln(Business debt)			0.030**				0.021*				-0.009	
			(0.012)				(0.011)				(0.013)	
Ln(Personal debt)			-0.008				-0.014				-0.020	
			(0.012)				(0.009)				(0.014)	
Ln(Bus debt_HighCap)				0.041**				0.080***				-0.010
				(0.019)				(0.025)				(0.016)
Ln(Bus debt_LowCap)				0.025*				-0.013				-0.012
				(0.014)				(0.015)				(0.015)
Ln(Pers debt_HighCap)				0.001				-0.018				-0.007
				(0.018)				(0.018)				(0.020)
Ln(Pers debt_LowCap)				-0.010				-0.009				-0.029
				(0.014)				(0.011)				(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Year and State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,614	5,614	5,614	5,614

This table reports the effect of debt (and its main decomposition into personal and business debt) on different economic outcomes (equation 4). We introduce heterogeneous effects by splitting industries into high and low capital intensive. OLS estimates are presented for Ln(Revenues) (columns 1 to 4), Market share (columns 5 to 8) and ROA (columns 9 to 12). The included controls and owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables and owner characteristic controls. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.8. 2SLS regressions

Dep. var.:	Ln(Debt)	Ln(Out_E)	Ln(Debt)	Ln(Out_E)
Model:	IV first stage	Second-stage IV	IV first stage	Second-stage IV
	(1)	(2)	(3)	(4)
Ln(County small bank branches 2004)	0.146**		0.124**	
	(0.060)		(0.061)	
Ln(Debt) instrumented		0.756**		0.793*
		(0.384)		(0.473)
Macroeconomic state controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Owner characteristics	No	No	Yes	Yes
Legal status fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
F-statistic	43.70		11.13	
Observations	5,618	5,618	5,618	5,618

This table reports 2SLS regression results. We use Ln(County small bank branches 2004) as an instrument for Ln(Debt). The macroeconomic state level controls are GDP per capita, personal income growth and unemployment growth. The other controls and owner characteristics are those summarized in Table 1.1. Table 1.A1 defines all variables and owner characteristic controls. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Figure 1.1. The governance role of debt in early stage firms

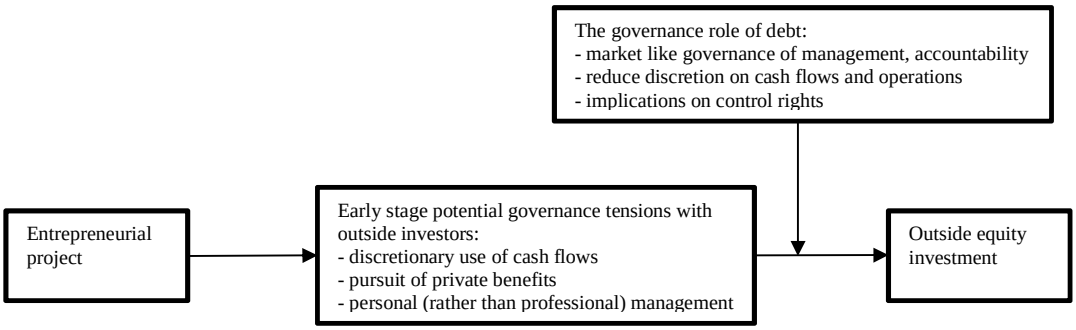
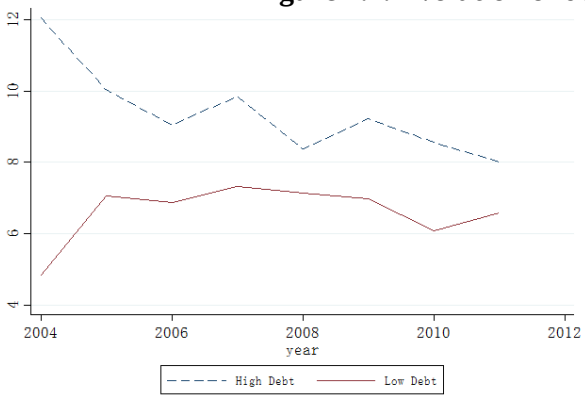
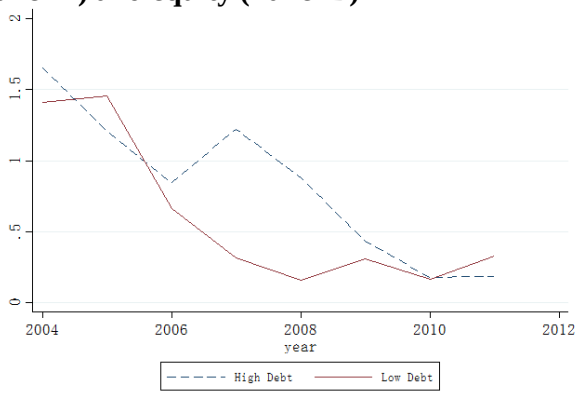


Figure 1.2. Evolution of debt (Panel A) and equity (Panel B)



This panel (A) presents the mean values of Ln(Debt) for high (dashed line) and low (solid line) debt groups using the matched samples. In 2004, we force this variable to differ across the two groups.



This panel (B) presents the mean values of Ln(Out_E) for high (dashed line) and low (solid line) debt groups using the matched samples. In 2004, we force this variable to be equal across the two groups.

1.7 Supplementary appendix

Table 1.A1. Definitions of variables

Main variables	
Ln(Debt)	Ln(Total debt in $ + 1)
Ln(Personal debt)	Ln(Personal debt in $ + 1)
Ln(Business debt)	Ln(Business debt in $ + 1)
Ln(Bank business debt)	Bank Business debt: Ln (bank business debt in $ + 1)
Ln(Non-bank business debt)	Non-bank Business debt: Ln (non-bank business debt in $ + 1)
Ln(Out_E>0)	Ln(Outside equity in $). It excludes firms with $0 in Outside equity
Ln(Out_E)	Ln(Outside equity in $ + 1)
Out_E_Dum	Dummy variable: 1 for positive $ amounts of outside equity, and 0 otherwise
Debt_Dum	Dummy variable: 1 for high debt, the highest quartile of Ln(Debt), and 0 for low debt, the lowest two quartiles
Other variables	
Crisis	Dummy variable: 1 for years 2007 – 2009, and 0 otherwise
Firm characteristics	
Ln(Revenues)	Ln(Revenues in $ + 1)
Profits	Profits amount in dollars
Credrisk	Dun & Bradstreet credit risk score: 1 (lowest) to 5 (highest probability of delinquency)
Employees	Number of employees
Hightech	Industries (NAICS) defined as technology employers and generators by the NSF's Survey of Industrial Research and Development
Ln(Cash)	Ln(Cash in $ + 1)
Ln(Accounts receivable)	Ln(Accounts receivable in $ + 1)
Ln(Inventory)	Ln(Inventory in $ + 1)
Ln(Fixed assets)	Ln(Fixed assets in $ + 1). Fixed assets is the sum of land, buildings, equipment and vehicles
Ln(Total assets)	Ln(Total assets in $ + 1)
ROA	Profits divided by total assets
Legal form	1: Limited Liability Company, 2: S-Corporation, 3: C-Corporation
Credit line	Dummy variable: 1 if the firm has an active bank credit line, and 0 otherwise
Market share	(Revenues / Industry-year revenues at 2-digit NAICS) x 100
Owner characteristics	
Owner age	Age of the primary owner
Years of industry experience	Primary owner's years of experience in industry
Week hours	Weekly hours dedicated to the venture by the primary owner
Start-up experience	Number of businesses previously created by the primary owner
Education	Educational level of the primary owner. 1: Less than 9th grade, 2: High school not finished, 3: High school, 4: Technical degree, 5: College not finished, 6: Associate degree, 7: Bachelor, 8: Graduate studies not finished, 9: Master, 10: Profess. schools/Doctorate.
Male	1: Male (primary owner), 0 otherwise
US born	1: US born (primary owner), 0 otherwise
Macroeconomic conditions	
GDP per capita	Yearly GDP per capita at state level collected from Bureau of Economic Analysis
Personal income growth	Yearly personal income growth at state level collected from Bureau of Economic Analysis
Unemployment growth	Yearly unemployment growth at state level collected from Bureau of Labor Statistics
High/low capital intensive industry	High and low capital intensive industries as defined in Appendix B of Acemoglu and Guerrieri (2007). Based on NAICS industry classification
Instrumental variable	
Ln(County small bank branches 2004)	Small bank branches per county in 2004. Similar to Berger et al. (2017), we define small banks as those with total assets below $1 billion. Source: Federal Deposit Insurance Corp. (FDIC).

Table 1.A2. Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Ln(Debt)	1.00														
2	Ln(Personal debt)	0.49	1.00													
3	Ln(Business debt)	0.50	0.22	1.00												
4	Ln(Bank business debt)	0.44	0.20	0.88	1.00											
5	Ln(Non-bank business debt)	0.20	0.08	0.40	-0.09	1.00										
6	Ln(Out_E)	0.06	0.07	0.10	0.04	0.13	1.00									
7	Out_E_Dum	0.06	0.08	0.10	0.04	0.13	0.98	1.00								
8	Crisis	0.06	0.01	0.04	0.05	-0.02	-0.03	-0.04	1.00							
9	Ln(Revenues)	0.18	0.01	0.16	0.15	0.04	-0.05	-0.05	0.06	1.00						
10	Profits	-0.03	-0.04	0.00	0.01	-0.01	-0.05	-0.04	0.01	-0.01	1.00					
11	Credrisk	-0.09	0.04	-0.05	-0.05	-0.01	0.01	0.02	-0.13	-0.10	0.01	1.00				
12	Employees	0.14	-0.02	0.17	0.16	0.06	0.08	0.06	0.02	0.20	-0.05	0.00	1.00			
13	Hightech	-0.01	-0.07	0.00	-0.02	0.03	0.06	0.05	0.01	0.03	-0.01	-0.09	0.02	1.00		
14	Ln(Cash)	0.14	-0.07	0.08	0.06	0.05	0.11	0.08	0.04	0.29	-0.01	-0.15	0.19	0.09	1.00	
15	Ln(Accounts receivable)	0.23	0.04	0.24	0.22	0.07	0.03	0.02	0.06	0.40	-0.01	-0.09	0.23	0.12	0.31	1.00
16	Ln(Inventory)	0.18	0.13	0.18	0.16	0.07	0.06	0.05	0.02	0.20	-0.02	0.03	0.13	-0.06	0.09	0.17
17	Ln(Fixed assets)	0.18	0.10	0.19	0.18	0.06	0.01	0.00	0.05	0.16	-0.02	-0.06	0.19	-0.07	0.12	0.19
18	ROA	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.03	0.00	0.00	0.00	-0.03	0.02	0.01
19	Owner age	0.01	-0.02	-0.01	-0.02	0.00	0.05	0.04	0.10	0.01	0.01	-0.09	0.01	0.03	0.05	-0.01
20	Years of industry exp.	-0.01	-0.09	0.00	0.00	0.00	0.05	0.04	0.01	0.05	-0.01	-0.06	0.06	0.14	0.08	0.13
21	Week hours	0.18	0.14	0.16	0.13	0.10	0.10	0.09	0.02	0.22	0.01	0.01	0.12	0.04	0.16	0.29
22	Start-up experience	-0.01	0.01	0.03	0.01	0.05	0.12	0.11	0.00	0.04	-0.02	0.01	0.05	0.02	0.05	0.02
23	Education	0.02	-0.04	-0.01	-0.03	0.05	0.10	0.09	-0.01	0.04	-0.01	-0.06	0.05	0.18	0.12	0.03
24	Male	0.06	-0.03	0.06	0.05	0.04	0.05	0.04	0.02	0.07	0.00	-0.02	0.06	0.07	0.12	0.10
25	US born	0.02	-0.01	0.01	0.02	0.00	-0.01	-0.01	-0.01	0.02	0.00	0.02	0.00	-0.06	0.00	0.01

	Variable	15	16	17	18	19	20	21	22	23	24
15	Ln(Accounts receivable)	1									
16	Ln(Inventory)	0.17	1								
17	Ln(Fixed assets)	0.19	0.2	1							
18	ROA	0.01	0.01	0.02	1						
19	Owner age	-0.01	0.04	0.04	0	1					
20	Years of industry exp.	0.13	-0.05	0	-0.02	0.4	1				
21	Week hours	0.29	0.17	0.14	0	-0.08	0.09	1			
22	Start-up experience	0.02	0.08	0.05	-0.03	0.18	0.04	-0.02	1		
23	Education	0.03	-0.07	-0.11	-0.01	0.11	0.01	-0.03	0.05	1	
24	Male	0.1	0.03	0.03	0	0.04	0.2	0.13	0.1	0.04	1
25	US born	0.01	-0.01	0.04	0	0.02	0.07	-0.03	0.03	-0.15	-0.04

This table reports correlations among the main variables (observations: 5,619). Table 1.A1 defines all variables.

Table 1.A3. Owner characteristics

	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum	Out_E_Dum
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Owner age	0.001***							0.000	0.000	0.000	0.000
	(0.000)							(0.000)	(0.000)	(0.000)	(0.000)
Years of industry		0.001***						0.000	0.001*	0.001*	0.001
experience		(0.000)						(0.000)	(0.000)	(0.000)	(0.000)
Week hours			0.001***					0.001***	0.001***	0.001***	0.001***
			(0.000)					(0.000)	(0.000)	(0.000)	(0.000)
Start-up experience				0.020***				0.019***	0.019***	0.018***	0.019***
				(0.003)				(0.003)	(0.003)	(0.003)	(0.003)
Male					0.024***			0.007	0.001	0.001	-0.001
					(0.007)			(0.007)	(0.007)	(0.007)	(0.007)
US born						-0.008		0.000	0.002	0.003	0.009
						(0.010)		(0.010)	(0.010)	(0.010)	(0.010)
Education							0.010***	0.010***	0.011***	0.011***	0.010***
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry fixed effects	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No	No	No	No	Yes	Yes
State fixed effects	No	No	No	No	No	No	No	No	No	No	Yes
Observations	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,619	5,619

This table reports OLS estimates the association between each (columns 1 to 7) and all (columns 8 to 11) owner characteristics variables with outside equity financing. Table 1.A1 defines all variables. Robust standard errors are presented in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.A4. Propensity score matched groups

	Propensity Score Sample					Full 2004 sample	
	Low debt group mean	Std. dev.	High debt group mean	Std. dev.	t-test p-value	Mean	Std.dev
Ln(Out_E)	1.410	(3.999)	1.656	(4.073)	0.559	1.199	(3.573)
Ln(Revenues)	7.931	(5.177)	8.175	(5.159)	0.652	7.719	(5.290)
Credrisk	3.245	(0.732)	3.277	(0.705)	0.664	3.279	(0.732)
Ln(Cash)	7.571	(4.156)	7.571	(3.711)	1.000	7.090	(4.003)
Ln(Inventories)	3.958	(4.929)	3.837	(4.658)	0.810	3.800	(4.783)
Ln(Total assets)	11.008	(2.221)	11.285	(1.292)	0.144	10.652	(2.115)
Employees	2.897	(8.558)	2.516	(3.63)	0.579	3.212	(9.862)
ROA	-0.341	(3.843)	-0.658	(2.538)	0.350	-0.355	(1.917)
Week hours	45.446	(24.858)	45.223	(23.443)	0.930	44.813	(23.390)
Start-up experience	1.049	(1.404)	0.967	(1.355)	0.571	0.993	(1.396)
Education	6.592	(2.130)	6.625	(2.063)	0.882	6.665	(1.988)

This table reports the means and standard deviations for the 184 treatment firms (high debt in 2004) and the matched 184 control firms (low debt in 2004) (equation 3). T-test p-values confirm that the matching process has been successful on the specified covariates since no significant differences across groups are observed. The sample is also matched by industry according to NAICS 2-digit codes. The two right columns include descriptive statistics of the full sample in year 2004 when the matching process is performed. Complete definitions for all variables are provided in Table 1.A1.

Chapter 2

2. The Information Content of Earnings Announcements in Newly Public Firms: Evidence from the JOBS Act

2.1. Introduction

Demand for corporate disclosure arises from information and incentive problems between managers and capital markets (Beyer et al. 2010; Graham et al. 2005; Healy and Palepu 2001; Kothari 2001). Firms provide new and relevant information to investors through regulated financial reports (Healy and Palepu 2001; Kothari 2001), which partly explains the relevance of financial reporting regulation ever since the first disclosure requirements were established for all traded companies in the Acts of 1933 and 1934. Indeed, many studies have documented the economic consequences of new disclosure mandates (e.g. the 1964 Securities Act Amendments), major extensions of such mandates (e.g. the Sarbanes-Oxley Act, SOX) and new sets of accounting standards (e.g. IFRS adoption) (Leuz and Wysocki 2016). However, we still know very little about disclosure deregulation events, mainly because they are rare episodes in accounting regulation (Fernandes et al. 2010). One obvious and important question that stems from such deregulatory episodes is whether accounting information remains as informative after relaxing disclosure requirements.

The Jumpstart Our Business Startups Act ("JOBS Act" or the "Act" hereafter) provides an appropriate setting to study the effect of disclosure deregulation on the informativeness of accounting information. The Act, signed into law on April 5, 2012, is one of the major changes in recent US disclosure regulation (Leuz and Wysocki

2016). Its main objective was to reduce the costs of going public by eliminating costly and excessively burdensome requirements for small firms, thus facilitating the access to public markets and incentivizing economic growth and job creation. Specifically, in its Title I, the JOBS Act relaxes mandatory disclosure requirements for Emerging Growth Companies (EGC hereafter), both in the IPO process and in the five subsequent years after the IPO. A firm qualifies as an EGC if it reports less than $1 billion in revenues in the year prior to its IPO. The EGC status lasts for five years unless the firm breaches thresholds related to revenues, debt, and public float.

Thus, the Act seems to change substantially the information environment of newly public firms, especially given that EGCs have accounted for 87% of the IPOs after the Act was implemented (Ernst & Young 2016). Critics of the JOBS Act claim that this poorer information environment may have negative side effects on investor protection security legislation, a view that appears to be shared by EGC firms. The following excerpt is taken from the 10-K filing of Editas Medicine Inc. on March 30, 2016; its wording is similar to that of many EGC firms:

> *"We are an "emerging growth company" under the JOBS Act of 2012, and we cannot be certain if the reduced disclosure requirements applicable to emerging growth companies will make our common stock less attractive to investors."*

In this study, I analyze whether the JOBS Act affected the information content of earnings announcements by allowing some firms to reduce their public disclosures in annual reports and proxy statements.[10] Following prior literature, I use the abnormal trading volume and the abnormal stock return volatility surrounding the earnings announcement event as a proxy for the information content of earnings (DeFond et al. 2007; Landsman et al. 2012; Landsman and Maydew 2002). I hypothesize a significant difference in the information content of earnings for EGC relative to full disclosure firms (FULLDISC) after the JOBS Act. In particular, I predict that this difference is driven by EGC firms' earnings being less informative after the Act. Economic reasoning suggests that an exogenous reduction in disclosure for EGC firms would promote private information acquisition, leading to information asymmetry among investors (Shroff et al. 2013). Such information asymmetries can create costs by introducing adverse selection into market transactions (Leuz and Verrecchia 2000;

[10] Similar to Leuz and Verrechia (2000), the notion of "scaled down" or "reduced" disclosure can be interpreted as either a decrease in the *quantity* or in the *quality* of disclosure (or both). I use both expressions for expositional convenience.

Shroff et al. 2013). In the extreme, these costs would only manifest for EGC firms by withdrawing the less informed investors from trading, creating weaker market reactions to earnings information at the announcement date. Accordingly, FULLDISC firms should not experience any difference in the information content of earnings after the Act as they are expected to report essentially the same information as before the Act.

Recent research has analyzed the consequences of the JOBS Act on different economic outcomes. Dambra et al. (2015) find a positive effect of the Act on the number of IPOs in the two years following the Act. Chaplinsky et al. (2017) find no evidence of a direct cost reduction for EGC firms in the IPO process, but instead document an 11% increase in indirect costs as measured by underpriced IPOs. Barth, Landsman, and Taylor (2017) find an increase in information uncertainty around the IPO event, reporting an average underpricing ranging from 6.3% to 12.9% of IPO proceeds for EGC firms. Dambra et al. (2017) find that changes in affiliated analysts' behavior (i.e. analysts whom the Act allowed to establish pre-IPO communications with EGC firms and other actors involved in the IPO process) increase post-IPO trading volumes and hence their compensation packages and brokerage firms revenues.

While all research on the JOBS Act focuses on the IPO event disclosure (i.e. IPO registration statement) and its short-term consequences, to the best of my knowledge, this is the first study to analyze the effect of the Act on the years following the IPO event (i.e. disclosure in 10-Ks and proxy statements). The analysis of the post-IPO is relevant because the provisions applicable to the IPO registration stage differ from those applicable to the newly public firm (i.e. five initial years after the IPO). In particular, after the IPO, EGC firms are allowed to delay compliance with Section 404(b) of SOX on audit attestation of internal controls, to delay new or revised accounting standards and new audit requirements. In addition, EGCs can disclose less information on executive compensation and are exempt from holding non-binding shareholder advisory votes (i.e. Say-on-Pay votes).[11]

I conduct the empirical analysis on a sample of US firms that filed for an IPO between 2002 and 2015. In the main analysis, I compare the information content of

[11] Prior studies on the JOBS Act capture exemptions used during the IPO registration phase and the intended exemptions IPO firms expect to use in the initial years of becoming a public firm (Barth, Landsman and Taylor, 2017; Chaplinsky et al., 2017). This information is derived from IPO firms' registration filings (i.e. S-1 filing). In contrast, I analyze the actual use of the provisions in the annual reports and proxy statements (i.e. 10-K and DEF 14A filings) subsequent to the IPO event. A summary of these disclosure provisions is available in Table 1. Section 2 provides a more detailed description of disclosure provisions available during the IPO registration stage and those available after the IPO.

earnings between EGC and FULLDISC firms after the Act. In order to show that the effect comes from the disclosure deregulation, I replicate my analysis for a pre-JOBS Act period (a period with no disclosure differences). This poses an identification challenge as I can not observe EGC firms before the Act. For that purpose, I construct a new variable, EGCwould, which identifies those firms that would have been an EGC firm had the JOBS Act been implemented before (i.e. I apply the EGC status thresholds in the pre-JOBS Act period).

Consistent with my hypothesis, I find a significant difference in the information content of earnings announcement for EGC relative to FULLDISC firms only after the JOBS Act (i.e. fiscal year 2012 and after). I argue that the effect is economically large: EGC firms experience a reduction of about 25% of the average abnormal traded volume in the days surrounding the earnings announcements. Likewise, the reduction is between 33% and 40% for the abnormal stock return volatility. To the best of my knowledge, this result provides the first empirical evidence that disclosure deregulation events have a negative effect on the information content of earnings. Interestingly, the difference does not seem to come exclusively from a decline in the information content of earnings of EGC firms but also from an increase in the information content of earnings of FULLDISC firms. I interpret this finding as suggestive that a deregulation event produces unexpected information spillover effects.

To provide further evidence that disclosure drives my main finding, I employ text analysis techniques to extract granular information regarding the provisions that each EGC firm applies in a given year. Descriptive statistics show that almost all EGC firms delay the audit attestation of internal controls (97% of EGC filings) and reduce the scope of executive compensation disclosure by providing information on less than five named executives (78% of filings) and no Compensation Discussion & Analysis (CD&A hereafter) section (67% of filings). By classifying EGC firms into lower and higher “provision takers”, I find that those applying more provisions experience a more severe decline in the information content of earnings. This result provides further support to the disclosure deregulation being a determinant of the lower information content of earnings.

Then, I examine two mechanisms that help reconcile the observed difference on the information content of earnings between EGC and FULLDISC firms. First, I look at business press as an alternative disclosure channel that further explains the decline in the information content of earnings for EGC firms. These firms may have incentives to

offset managers' concerns for the reduced mandatory reporting by voluntarily disclosing information through alternative channels as, for example, the media. I explore heterogeneous effects of media types (e.g. news flashes, full articles or press releases) and news topics (e.g. earnings or revenue-related). I find that only after the Act, EGC firms issue more revenue-related press releases in the 180 days before the announcement date (relative to FULLDISC firms). This information may already be impounded into stock prices before the announcement event, leading to less informative earnings for EGC firms. I interpret this voluntary disclosure negative effect on the information content of earnings as incremental to the main disclosure deregulation effect.

Finally, I investigate a second mechanism that helps to explain the unexpected increase in the information content of earnings in FULLDISC firms: analyst coverage. I focus on this variable since prior literature find a robust positive association between the number of analysts and the information content of earnings (DeFond et al. 2007; Landsman et al. 2012). I find a significant increase in the number of analyst following FULLDISC firms after the Act along with a decrease in the number of analysts following EGC firms. This suggests that the JOBS Act regulatory change produced an unintended spillover effect. Moreover, I also show evidence of a change in the ownership structure of EGC firms: after the Act, ownership in EGC firms includes a larger presence of institutional investors. Such investors have been shown to benefit from low public disclosure (i.e. they have easier access to a now more valuable private information (Ali et al. 2004; Bushee and Goodman 2007)). As a result, analysts may lose their incentives to follow EGC firms with high presence of institutional ownership (i.e. there is less need for analyst information in firms with highly informed investors) in favor of FULLDISC firms. Thus, I argue that the Act may have incentivized more (less) analysts to follow FULLDISC (EGC) firms, thus increasing (reducing) the information content of earnings for each type of firm.

This paper contributes to two streams of literature. First, in the corporate disclosure literature, few studies have analyzed the economic consequences of (admittedly infrequent) disclosure deregulation events (Fernandes et al. 2010). To the best of my knowledge, this is the first study that documents a negative association between corporate disclosure deregulations and the information content of earnings. In addition, my study uses the JOBS Act as a setting to observe how corporate disclosure dynamics work: the results suggest that EGC firms adopt the disclosure provisions and

at the same time they intensify voluntary disclosure (through the business press). While the use of voluntary disclosure has long been studied in the corporate disclosure literature (Beyer et al. 2010; Healy and Palepu 2001), managers' choice to substitute mandatory with voluntary disclosure is less documented. Also, my study provides evidence of a spillover effect by revealing an increase (reduction) in the number of analysts following FULLDISC (EGC) firms. This finding contributes to fill a gap in the accounting literature that studies spillover, externalities and network effects of regulatory interventions (Leuz and Wysocki 2016).

Second, I also contribute to the JOBS Act literature. Contrary to prior studies, which concentrate exclusively on the IPO event and mainly on the short-term consequences of becoming a public company (e.g. IPO underpricing and volatility, IPO direct versus indirect costs), my study is the first to document the evolution of EGC firms after the Act, that is, during the five years following the IPO. The different nature of the disclosure provisions eligible in the IPO event relative to those eligible in the five subsequent years justifies a differentiated analysis, in that different provisions might lead to differences in investors' reaction.

The remainder of the paper is as follows; Section 2 presents the JOBS Act, a literature review on the information content of earnings and the main predictions. Section 3 introduces the main variables of interest and the research design. Section 4 describes the sample composition. Results are presented in Section 5 jointly with tests that discard alternative explanations. Section 6 explores the two mechanisms that help to explain the main finding of the paper. Section 7 concludes.

2.2 Institutional setting, related literature and main predictions

2.2.1 The JOBS Act

The Jumpstart Our Business Startups Act, better known as the JOBS Act, was signed into law on April 5, 2012. The Act includes several sections (Titles) of regulations aimed at facilitating access to financing for small and medium enterprises.[12] In this paper, I focus on "Title I. Reopening American capital markets to emerging growth

[12] For example, Title II allows private firms to engage in general solicitation (advertising) of their stock when seeking equity financing (effective from September 23th, 2013). In its Title III, the Act amends the Securities Act of 1933 by relaxing individual conditions to become an equity investor. After the Act, essentially any American can invest in private firms' equity offerings (investing up to $2,000 or a maximum of a 5% of annual income or net worth, whichever is lower).

companies", which promotes access to public markets for small firms. In particular, Title I of the Act establishes a new category of issuer, the Emerging Growth Company (EGC), and relaxes compliance and certain disclosure requirements for firms filing for an IPO and in their subsequent annual reports and proxy statements. To be eligible, an IPO-filing company must report annual revenues lower than $1 billion in its last fiscal year before the IPO.[13] The EGC status lasts for five years if the firm does not breach any of the following requirements: (a) annual revenues being higher than $1 billion, (b) issuing more than $1 billion in non-convertible debt over the last three years, and (c) becoming a large accelerated filer (i.e. having a public float greater than $700 million). Once the status has been lost, it cannot be regained.

The provisions are not only targeted at the IPO registration stage (e.g. S-1 filings) but also at subsequent reporting requirements (e.g. 10-K filings or proxy statements). In the IPO event, the Act allows EGC status firms to: (a) confidentially file IPO registration drafts and amendments until the 15th day before the firm conducts a road show (before the Act, almost all firms had to publicly disclose all their IPO registration filings),[14] (b) interact with potential qualified investors and analysts before a definite IPO registration statement is filed (before the Act, such communications were not allowed), (c) only disclose two years of executive compensation for three named executives and no CD&A section (before the Act it was three years of executive compensation for five named executives plus the CD&A section), and (d) provide two years of audited financial statements (before the Act, the minimum was three years or the life of the company if shorter).

During the five years after the IPO event, EGC status firms are eligible to apply the following provisions: (a) not comply with Section 404(b) of SOX that mandates audit attestation of the effectiveness of internal controls over financial reporting,[15] (b)

[13] This revenue threshold has been adjusted for inflation to $1.07 billion effective as of April 12th, 2017. See https://www.sec.gov/rules/final/2017/33-10332.pdf. Last accessed: September 2017

[14] Some privately listed foreign firms and government-owned foreign firms were exempt from this restriction (Barth, Landsman and Taylor, 2017). Since July 10th, 2017, all companies filing for an IPO may be eligible to apply this provision. See https://www.sec.gov/corpfin/announcement/draft-registration-statement-processing-procedures-expanded#_ftn. Last accessed: September 2017

[15] Section 404(b) of SOX assures that proper internal controls are put in place, helping companies anticipate financial fraud and directly improving the reliability of financial statements (Iliev 2010). A firm may save more than half a million dollars per year by not complying with Section 404(b) of SOX (Gao 2016; Iliev 2010), a considerable expense considering a median revenue amount of approximately $35 million at the IPO event in 2015 and 2016 (Ernst & Young 2016).

delay application of new or revised accounting standards set by the FASB,[16] (c) delay adoption of new audit requirements or mandatory audit firm rotation as dictated by the Public Company Accounting Oversight Board, (d) be exempt from the CD&A section and only disclose executive compensation information for three rather than five named executives, and (e) be exempt from holding non-binding advisory votes as dictated by the Dodd-Frank Act of 2010 (i.e. say-on pay votes). Table 2.1 provides a summary of the post-IPO provisions available to EGC companies.

Given the significant differences between the provisions applicable to the IPO registration stage and those applicable to the newly public firm (i.e. five years after the IPO), the analysis of the post-IPO years is likely to yield additional insights regarding the economic effects of the Act's provisions and how investors react to the reduced disclosure. To the best of my knowledge, this is the first paper that analyzes the effects of the Act in the years following the IPO.

Recent research shows that the JOBS Act effectively increased the number of IPOs in the two years following the passage (Dambra et al. 2015). In particular, the authors find that the Act promoted 21 additional IPOs registration in years 2013 and 2014, representing a 25% increase over the 2001-2011 period. However, other studies have also documented unintended consequences of the JOBS Act. First, Chaplinsky et al. (2017) find no evidence of a direct cost reduction in EGC firm IPOs, but in contrast they document an 11% increase in indirect costs as measured by IPO underpricing.[17] Second, the confidential filing of the IPO prospectus, together with the reduced disclosure, motivated an increase in the information uncertainty surrounding EGC firms in and immediately after the IPO event, producing underpricings ranging from 6.30% to 12.93% of IPO proceeds for EGC firms (Barth, Landsman, and Taylor 2017). Third, Dambra et al. (2017) find that affiliated analysts (i.e. EGC firm analysts whom the Act allowed to establish pre-IPO communications) change their behavior to favor higher post-IPO trading volumes and hence brokerage revenues, which are important inputs in analyst compensation packages. Fourth, the JOBS Act modified the way in which firms

[16] This provision raises concerns on the comparability of financial statements between EGCs and all other public companies. Although no major accounting regulatory changes were made effective in the 2012-2015 period of the study, there are some to come (e.g. new lease accounting, effective from December 2018). Since March 31, 2017, the SEC mandates filers to explicitly state the use of this provision on the cover page of the annual report, together with the EGC status.

[17] One of the main purpose of the Act is to lower the costs of going public (e.g. audit or legal costs) as these costs can be very significant for small and medium sized firms. These costs average $3.9 million plus the underwriter fees, usually set between 4-7% of the gross proceeds (PricewaterhouseCoopers, 2015)

file IPO prospectuses, providing less accounting information and a more risk related wording in their textual disclosures. The study finds that the latter change in textual disclosure is associated with greater IPO underpricings (Agarwal et al. 2016). Fifth, Gipper (2016) analyzes the role of the CD&A section, one of the disclosure provisions set by the Act, in executive compensation packages. He finds that compensation disclosure is associated with increases in executive pay levels as the firm anticipates potential competing offers.

2.2.2 The information content of earnings announcements literature

The notion of the information content of an event relates to whether, and how, such event conveys new information to market participants. If this new information changes investors' expectations and behavior, thus, one would expect changes in the level and variability of stock prices or trading volume over a short time period around the announcement event (Beaver 1968; Kothari 2001). Beaver (1968) carefully distinguishes the effect of new information on price volatility (resulting from changes in average market expectations) and on trading volume (resulting from changes in the expectations of individual investors).

This conceptual distinction has generated a stream of research related to the information content of earnings to work which uses two main variables of interest: abnormal stock price return volatility and abnormal trading volume. For instance, Landsman and Maydew (2002) conclude that earnings become increasingly informative over the period 1972 to 1998 after controlling for changes in the composition of firms across time (e.g. firm size, intangible intensity and presence of losses). DeFond et al. (2007) study cross-country differences in the information content of earnings. They find that countries with higher quality earnings and enforced insider trading laws are associated with more informative earnings while more frequent interim financial reporting is negatively associated with the information content of earnings. Landsman et al. (2012) also present a cross-country study analyzing the effects of IFRS adoption. As they predict, those countries that mandate IFRS adoption (i.e. standards associated with higher financial reporting quality and comparability) experience a greater increase in the information content of earnings announcements relative to those who kept domestic standards. Altogether, it seems that informationally rich environments (e.g. IFRS

adoption, higher quality earnings) produce more informative earnings, which helps determine the basis of my predictions.

2.2.3 Main predictions

I hypothesize a significant difference in the information content of earnings between EGC and FULLDISC firms after the JOBS Act. In particular, I hypothesize that this difference stems from EGC firms having less informative earnings as a result of the scaled down disclosure. Also, I expect the difference in the information content of earnings to be more salient in firms that make greater use of disclosure exemptions. This is consistent with prior literature which documents that those small reporting companies that use disclosure exemptions more extensively following the Smaller Reporting Company Regulatory Relief and Simplification rule (i.e. disclosure simplification rules for Smaller Reporting Companies effective since 2008) experienced a more pronounced increase in market illiquidity after the rule (Cheng et al. 2013). Finally, all else equal, FULLDISC firms should not experiment any significant difference after the Act since they continue disclosing the same information under the same set of disclosure requirements.

Economic reasoning is consistent with the above predictions in that an exogenous reduction in EGC firms' disclosure promotes private information acquisition, leading to information asymmetries among investors (Shroff et al. 2013). Institutional investors are likely to cause the asymmetric information problem as they can obtain private information more easily and hence execute profitable trading strategies (Ali et al. 2004; Bushee and Goodman 2007). This asymmetric information environment creates adverse selection costs and lowers market transactions by preventing less informed investors to trade in EGC firms' stocks (Leuz and Verrecchia 2000; Shroff et al. 2013). Accordingly, I do not expect any change in the information content of earnings for FULLDISC firms as they are not subject to the regulatory intervention.

I explore two mechanisms to better understand the effect of the JOBS Act on the information content of earnings: business press and analyst coverage. First, media coverage has received increasing attention in the finance and accounting literatures as there is substantial evidence that the business press provides information about firms' fundamentals incremental to other sources of information (Bushman et al. 2016; Tetlock et al. 2008). According to Drake et al. (2014), the business press can impact capital

markets by broadly disseminating firm-generated information and by creating new information for market participants.

I expect EGC firms to increase the amount of information issued through the business press before the earnings announcement in an attempt to anticipate and compensate for a reduced mandatory disclosure. This raises the question of why managers would eliminate previously mandated disclosure and at the same time, increase voluntary disclosure. Similar to the discussion provided in Barth, Landsman, and Taylor (2017), I argue that the costs of previous mandatory disclosure (e.g. audit of internal controls, disclosure of potential internal control weaknesses or excessive executive compensation packages) might be above the benefits of disclosure. In contrast, and holding constant the content of the information, having a greater presence in the media (e.g. press releases) seems less costly relative to the potential benefits. Some of such benefits are documented in Kothari et al. (2009), who find that favorable press disclosures result in lower costs of capital. Similarly, Bushee et al. (2010) find that greater press coverage reduces information asymmetries around earnings announcements. Altogether, it seems that EGC firms have incentives to compensate their post-Act reduced mandatory disclosure with alternative (voluntary) sources of information such as the business press. I claim that this new voluntary disclosed information (released through press coverage) may be impounded into the stock price before the announcement date and hence, EGC firms experience lower informative earnings relative to FULLDISC firms. I interpret this negative effect on the information content of earnings as incremental to the main disclosure deregulation negative effect. A similar reasoning is also observed in DeFond et al. (2007), who document that earnings announcements in countries with higher frequent interim financial reporting show lower information content of earnings as a result of information being already available in the market prior to the announcement date.

Second, I study analyst coverage as an alternative mechanism that may affect the information content of earnings. Two reasons motivate the study of this variable. First, prior literature documents a positive association between the number of analysts following and the information content of earnings (DeFond et al. 2007; Landsman et al. 2012). It may be that investors of firms with richer information (i.e. more analysts following) may be able to more quickly interpret the valuation implications of the announced earnings, therefore generating a stronger market reaction in the earnings announcement event (Barth, Landsman, Raval and Wang, 2017). Second, Dambra et al.

(2017) document that analyst behavior changed after the Act, producing higher post-IPO trading volumes and hence their compensation packages and brokerage firms revenues. Altogether, it seems that the number of analysts can motivate a change in the information content of earnings of either EGC or FULLDISC firms. However, no prior study on the JOBS Act has examined whether the Act may have had an effect on the number of analysts following the two types of firms. I therefore do not document a specific prediction for EGC or FULLDISC firms. To the extent that either EGC or FULLDISC firms receive greater attention from analysts after the Act, I would expect their earnings to be more informative and vice versa.

2.3 Main variables

A primary goal of this research is to analyze whether differences in the information content of earnings originate between EGC and FULLDISC firms after the JOBS Act. In the main analysis, I compare EGC to FULLDISC firms in the fiscal years after the Act, expecting a significant difference between the two. To show that the effect comes from the disclosure deregulation, I replicate my analysis for a pre-JOBS Act period (a period with no disclosure differences). This poses an identification challenge as the category of EGC firms did not exist before the Act. To circumvent this difficulty, I use the EGC status thresholds to identify those firms that would have filed under EGC status had the JOBS Act been implemented before (i.e. firms with annual revenues lower than $1 billion, have not issued more than $1 billion in non-convertible debt over the previous three years and are not large accelerated filers). Conversely, I will obtain those firms that would have been non EGC before the Act. I call these pre-JOBS Act observations EGCwould and NEGCwould respectively. I validate this EGCwould identification procedure by comparing it to the post-JOBS Act period (where I observe the EGC status). The procedure successfully classifies 97.5% of the post-Act EGC firm-year observations, thus, validating the measure. The main analysis estimates the difference in the information content of earnings of EGC relative to FULLDISC firms after the Act (disclosing differences period), where I expect to find a significant difference. I replicate the test for EGCwould and NEGCwould before the Act (a “placebo” period with no disclosing differences), where I do not expect differences between the two groups.

The information content of earnings announcements measure is constructed with the 3-day abnormal trading volume and abnormal return volatility surrounding the earnings announcement date [-1,0,1] (Landsman et al. 2012; Landsman and Maydew 2002). For the estimation, I also define a non-event period as day -120 through day -21 and +21 through day +120 relative to announcement day t = 0. I drop the 40 days surrounding former and future earnings announcement to obtain a non-event period window net of any earnings announcement effect.[18] First, I define abnormal trading volume (AVOL) as the average daily trading volume during the firm's earnings announcement window [-1,0,1] scaled by the average trading volume during the non-event period:

$$AVOL_{it}=\bar{V}_{it}/V_i \tag{2.1}$$

Stronger market reactions are associated with higher values of AVOL, that is, the market abnormally reacts by trading above the average trading volume observed during the non-event period.

Second, I define abnormal return volatility (AVAR) as the stock return volatility over the event period [-1,0,1] for firm i at day t scaled by the stock return volatility of that firm over the non-event period. I compute the stock return volatility over the event period as the average of the squared prediction errors ($\bar{u}_{it}^2$) from the market model-adjusted returns during the event period [-1,0,1]. Following Landsman and Maydew (2002) and Landsman et al. (2012), I compute the market model-adjusted return as $u_{it} = R_{it} - (\alpha_i - \beta_i R_{mt})$, where R_{it} is the stock return of firm i for day t, R_{mt} is the equal-weighted market return for day t, and α_i and β_i are firm's i market model parameter estimates, each of which calculated during the non-event period. Then, the stock return volatility for firm i during the non-event period (σ_i^2) equals the variance of the residuals returns from the firm's market model estimated over the non-event period [-120 to -21 , +21 to +120]:

$$AVAR_{it} = \bar{u}_{it}^2 / \sigma_i^2 \tag{2.2}$$

Similar to AVOL, higher abnormal stock return volatilities (AVAR) are associated with more informative earnings. Likewise, less informative earnings produce low abnormal stock reactions at the announcement date.

[18] The data extraction process obtains quarterly earnings announcement dates from Compustat quarterly and drops the [-20,+20] days surrounding former and future quarterly earnings announcement periods.

2.4 Research design

2.4.1 The information content of earnings pre- and post-JOBS Act

I hypothesize a significant difference in the information content of earnings for EGC relative to FULLDISC firms only after the JOBS Act. Specifically, I compare the difference in the information content of earnings between EGCwould and NEGCwould firms before the JOBS Act (i.e. years 2002-2011) and between EGC and FULLDISC firms after the Act (years 2012-2015).[19] I estimate the following model specifications:

$$\mathrm{AVOL_{it}}=\beta_0 + \beta_1 \mathrm{EGC}_{it} + \sum_k \beta_k X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (2.3)$$

$$\mathrm{AVAR_{it}}=\beta_0 + \beta_1 \mathrm{EGC}_{it} + \sum_k \beta_k X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (2.4)$$

where AVOL and AVAR are abnormal trading volume and abnormal return volatility for firm *i* in year *t*. $\mathrm{EGC_{it}}$ is an indicator variable equal to 1 for EGCwould firms in the 2002-2011 sample (0 for NEGCwould). As both EGCwould and NEGCwould firms fully disclose their financial information, I expect β_1 to not be significant in the 2002-2011 sample. In contrast, $\mathrm{EGC_{it}}$ equals 1 for EGC firms in the 2012-2015 sample and 0 for FULLDISC firms in or after 2012). I predict a negative and significant β_1 coefficient for this second sample (after the Act), resulting from EGC firms providing a scaled down mandatory disclosure.

Equations (3) and (4) include a set of control variables, X_{it}, identified by the literature as potentially affecting the main variables of interest. First, SIZE is the natural logarithm of the market value of equity at fiscal year-end. Prior literature documents mixed results on this variable so I do not make any specific prediction for SIZE (Landsman et al. 2012). REPLAG is the lag in number of days between the fiscal year-end date and the earnings announcement date. As documented in DeFond et al. (2007), a longer reporting lag increases the likelihood of obtaining earnings information prior to the announcement date (e.g. analyst or management forecasts may have become available). As such, I predict a negative coefficient on this variable. LEVERAGE is also included as Landsman et al. (2012) report a positive association with AVAR and AVOL in some specifications. LOSS_D is an indicator variable that equals 1 when a firm experiences losses, which has been documented to be less informative about the firm's future prospects (Hayn, 1995). Unexpected earnings (UE) is the absolute difference

[19] I avoid using a "differences-in-differences" specification since there is no group that unambiguously received a treatment, that is, EGC firms only appear after the JOBS Act.

between actual earnings per share and the most recent mean analyst estimate of earnings per share, scaled by the closing stock price on the earnings announcement date. DISP is the standard deviation of analysts' earnings per share forecasts scaled by the closing stock price on the earnings announcement date. NUMEST is the number of analyst following a firm in the most recent quarter closer to the earnings announcement. I also include some time variant firm controls such as ROA (profitability measure) and BIG4 (whether the firm is audited by a big4 audit company). Both equations include firm and year fixed effects to control for firm and macroeconomic unobserved heterogeneity. Standard errors are clustered at the firm and year-month levels. Appendix A defines all variables in more detail.

I further investigate the source of the potential difference in information content after the JOBS Act. This could be tested by estimating versions of equations (3) and (4) for each group of firms (EGC and FULLDISC) across time and testing whether a significant change in AVOL and AVAR originates after the Act (i.e. in or after fiscal year 2012). While this approach is feasible for FULLDISC firms, for which data are available since 2002, it is infeasible for EGC firms, since we do not observe EGC firms before 2012. Therefore, I estimate the following two equations restricting the sample to FULLDISC firms:

$$\mathrm{AVOL_{it}} = \beta_0 + \beta_1 \mathrm{POST}_{it} + \sum_k \beta_k X_{it} + \alpha_i + \varepsilon_{it} \tag{2.5}$$

$$\mathrm{AVAR_{it}} = \beta_0 + \beta_1 \mathrm{POST}_{it} + \sum_k \beta_k X_{it} + \alpha_i + \varepsilon_{it} \tag{2.6}$$

where AVOL and AVAR are abnormal trading volume and abnormal return volatility for firm *i* in year *t*. $\mathrm{POST_{it}}$ is an indicator variable equal to 1 in fiscal years 2012 to 2015 (0 otherwise). I expect β_1 to not be significant for FULLDISC firms as no change in disclosure is expected after the JOBS Act. Controls (X_{it}) are those described in equations (3) and (4). I also include firm fixed effects to control for firm unobserved heterogeneity, but not year fixed effects to avoid confounding effects with the $\mathrm{POST_{it}}$ variable of interest. Standard errors are clustered at the firm and year-month level. Appendix A defines all variables.

To provide some evidence that the difference in information content comes from EGC firms showing lower informative earnings after the Act, I use a t-test to compare the mean levels of AVOL and AVAR between EGCwould and EGC firms.[20]

[20] I complement this AVOL and AVAR t-tests analysis by matching EGCs to single EGCwould firms. See the analysis presented in section 5.3.2.

2.4.2 JOBS Act disclosure provisions

In order to provide further evidence that disclosure drives my main finding, I analyze the JOBS Act disclosure provisions into more detail. I parse all 10-Ks and DEF 14A filings to construct a dataset that contains information of which exemption(s) each EGC uses in a given year. In particular, I look for standardized keywords or short sentences that firms use when expressing their use (or not use) of an exemption. Manual inspection of the filings is performed when needed from the EDGAR website.

Economic reasoning predicts that those EGC firms that take more advantage of disclosure provisions should experiment a more severe decline in the information content of earnings. I use the output from the parsing process to classify EGC firms into "low provision users" (EGC which use one to three disclosure provisions) and "high provision users" (EGC which use four or five disclosure provisions). I then split EGCs into two indicator variables EGC_{Low} and EGC_{High}. I establish three provisions as the cutoff between low and high provision users since the data suggest that most EGCs apply three provisions (i.e. audit attestation of internal controls, the reduced disclosure on executive compensation and not providing the CD&A section). I then reestimate equations (3) and (4) substituting EGC for the two indicators EGC_{Low} and EGC_{High}. In light of the stickiness in the usage of disclosure provisions (i.e. the decision to apply one provision is persistent over the whole EGC status fiscal years), I provide the results of both a pooled OLS and a firm fixed-effects specifications.

2.4.3 Mechanisms: Business press and analyst coverage

I explore a mechanism that, additionally to the effect of the reduced mandatory disclosure, may help to explain the observed decline in the information content of earnings. EGC firms may have incentives to offset the reduced mandatory reporting by voluntarily disclose information through other sources like the media. Some studies document the benefits of business press disclosure in reducing information asymmetries (Bushee et al. 2010) or financing costs (Kothari et al. 2009)). Accordingly, I predict EGC firms to increase the amount of press coverage before the earnings announcement dates to compensate, in a less costly manner, for the reduced mandatory disclosure.

In an attempt to exploit heterogeneous effects, I use the total count number of press items (ALLPRESS) and press releases (PRESS_REL) from the 180 to the 2 days before the announcement. This time window ensures that the information contained in

the press is sent to the market prior to the event.[21] I distinguish between ALLPRESS and PRESS_REL because press releases have been documented to be a proxy for firm-initiated voluntary disclosure (Drake et al. 2014; Shroff et al. 2013), while other types of press forms such as full articles, news flashes or tabular material may be considered press-initiated (Drake et al. 2014). In addition, I also analyze the content of the news classifying them by topics. I select the four most relevant topics (i.e. those which correspond to a higher number of press items) from the Ravenpack Dow Jones Edition database for the analyzed sample of firms. These four topics are: earnings, revenues, technical analysis and insider-trading.

To test this mechanism, I use an approach similar to that in equations (3) and (4). Specifically, I compare the difference in media coverage between EGCwould and NEGCwould firms before the JOBS Act (i.e. years 2002-2011) and between EGC and FULLDISC firms after the Act (years 2012-2015). I estimate the following model:

$$\text{PRESS\_DV}_{\text{it}}=\beta_0 + \beta_1 \text{EGC}_{it} + \sum_k \beta_k \text{CONTROLS}_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2.7}$$

where $\text{PRESS\_DV}_{\text{it}}$ is either ALLPRESS (all press items) or PRESS_REL (only press releases) for firm *i* in year *t*. EGC_{it} is the indicator variable used in equations (3) and (4). As both EGCwould and NEGCwould firms fully disclose their financial information, I expect β_1 to be not significant for the 2002-2011 sample (ceteris paribus, both types of firms may experience a similar amount of media coverage before the Act). In contrast, I predict a positive and significant β_1 coefficient after the Act as a result of EGC firms willing to disclose more information before the earnings announcement date and hence compensate for the reduced mandatory disclosure. This would translate into a weaker market reaction in the announcement date as information would already be impounded into the stock price by the time of the announcement event. Appendix A defines all variables.

To further explore potential mechanisms by which the JOBS Act may affect the information content of earnings, I look at the analyst coverage. Despite not giving a precise prediction on the effect, I argue that any positive (negative) change in the number of analysts following EGC or FULLDISC firms may lead to an increase (decline) in the information content of earnings. To test this mechanism, I check whether significant differences between the two groups of firms originate after the Act.

[21] Conclusions are not qualitatively affected to the use of press items issued 90 or 60 days (instead of 180) before the earnings announcement date.

I regress the analyst variable on an indicator variable that equals 1 for EGC firms (0 for FULLDISC firms). To identify that the effect comes from the JOBS Act, I replicate my analysis in a pre-JOBS Act period (where no disclosure differences exist). To observe whether the difference comes from EGCs or FULLDISC firms, I employ an analysis similar to that of equations (5) and (6): t-test differences between EGCwould (pre) and EGC firms (post-Act period) and a regression with a POST indicator variable (measure of the change between the pre and the post period) for FULLDISC firms.

2.5 Sample

I use SDC Platinum to construct my sample of all US IPOs that listed common stock for the first time between 2002 and 2015. The sample starts in 2002 because that is the first year for which data on large accelerated filers are available in Audit Analytics. Information on whether a company is a large accelerated filer is needed to construct the EGCwould variable (i.e. being a large accelerated filer is one of the EGC status thresholds).[22] I subsequently match the IPO information to Compustat and drop firms with negative revenues. Consistent with Barth, Landsman, and Taylor (2017) and Dambra et al. (2017), I require issuers to file under form S-1 and exclude leveraged buyouts, closed and opened-end funds, trusts and special purpose vehicles (i.e. SIC codes 6091, 6371, 6722, 6726, 6732, 6733 and 6799). I use Audit Analytics to obtain the EGC status indicator variable and identify those firms that are a large accelerated filer. After this screening process, there are 1,521 remaining firms that are merged to CRSP and I/B/E/S Unadjusted Summary and Unadjusted Actual file (I adjust data for stock splits using CRSP adjustment factor). Following the practice in the literature, I require a minimum of three analysts following each company, which yields a final sample of 1,321 firms. Finally, I use Ravenpack Dow Jones Edition to obtain media coverage data. I can match these media data on 838 unique firms and 4,456 firm-year observations. As this final criterion substantially reduces the number of firms (a 36.5% decrease), I only use the reduced Ravenpack sample when analyzing the media mechanism.

I empirically test my predictions on the full sample (i.e. IPOs since 2002) and also on a reduced subsample of firms that went public in the years surrounding the Act (i.e. this subsample starts in July 2009). The rationale behind using this subsample is that

[22] Starting the sample in year 2002 does not remove relevant information from my sample since the main goal of the paper is to analyze the post-Act sample (i.e. effect after the Act).

pre-JOBS Act firms that went public after July 2009 are more likely to be comparable in their fundamentals to EGC firms (i.e. their IPOs are closer in time) and were not a public company during the financial crisis. Following Barth, Landsman, and Taylor (2017), I use July 2009 as the post crisis period, which is consistent with NBER business cycle dates.[23] Table 2.2 presents descriptive statistics for AVOL and AVAR and control variables. Panel A shows statistics for the full sample while Panel B reports the post crisis sample. Values are comparable across samples, with the exception of some business press variables. In particular, Panel A reports an average of 224.48 articles and 34.78 firm press releases in the 180 days prior to the announcement date, while Panel B shows averages of 282.31 and 67.84 respectively. This difference is mostly explained by the effect of two FULLDISC firms (Facebook and Linkedin) that went public after the crisis. These firms concentrate a lot of attention from the media and increase the average press coverage for the more reduced number of observations in the post crisis sample. Other statistics (median, quartiles) do not show such important differences. As for the analysis, these differences do not affect my inferences as long as I compare firms "within" the pre or post-JOBS Act sample period separately.[24]

2.6 Main analysis and discussion

2.6.1 The information content of earnings pre- and post-JOBS Act

Figure 1 shows the evolution of means of AVOL (upper graph) and AVAR (lower graph) for firms that went public in or after 2002. I compute separate yearly averages for EGCwould (straight line) and NEGCwould (dashed line) in fiscal years before 2012, and EGCs (straight line) and FULLDISC (dashed line) in or after fiscal year 2012. I observe that the information content of earnings do not differ between EGCwould and NEGCwould firms in the years before the Act. However, in 2012, the first year in which the JOBS Act allows for the reduced disclosure, the evolution of the information content of earnings differs substantially between EGC and FULLDISC firms. This figure is suggestive of the effect the Act may have had on the information content of earnings for newly public firms.

Table 2.3 shows the results of estimation of equations (3) and (4), which examine the difference in information content of earnings between the groups of firms depicted

[23] Source: http://www.nber.org/cycles.html. Last accessed: September, 2017.
[24] Results are robust to the exclusion of both firms.

in the graphs. Panel A reports results for the 2002-2011 period in which there were no disclosure differences. As predicted, the coefficient on EGCwould is statistically insignificant both in the full (columns (1) and (2)) and the post crisis sample (columns (3) and (4)). This result indicates that there is no evidence of differences in the information content of earnings prior to the Act between EGCwould and NEGCwould firms. This is in line with my expectations, given that no differences in disclosure exist before the Act. Panel B reports the results of the post-JOBS Act period. The estimated coefficients on the EGC indicator variable is now negative and statistically significant in both samples (coefficients of -0.544 and -0.477 for AVOL and -2.418 and -1.951 for AVAR; t-stats of -4.34, -1.94, -3.70 and -1.71 respectively). The magnitude of the coefficients suggests a large decline in the information content of earnings for EGC relative to FULLDISC firms. For example, the estimated AVOL coefficient of -0.544 in column (1) represents a reduction of about 25% of the average abnormal traded volume in the days surrounding the earnings announcements. Likewise, the estimated coefficient for AVAR implies a reduction of between 40% and a 33% of average abnormal volatility (full and post crisis sample respectively). Untabulated pooled regressions (i.e. regressions which omit firm fixed effects but include industry fixed effects) corroborate these results. Overall, I find support for the prediction that the scaled down disclosure implied by the usage of the JOBS Act's provisions produces less informative earnings for EGC firms.

In order to understand whether this difference is driven by EGCs or FULLDISC firms (or both), I show in Table 2.4 the results of analysis that compare the informativeness of earnings before and after the JOBS Act for the two types of firms. Panel A of Table 2.4 shows univariate t-tests which compare average AVOL and AVAR for EGCwould observations before the Act (fiscal years prior to 2012) relative to EGC observations (fiscal years 2012-2015). The results suggest that indeed AVOL decreases significantly for EGC firms (compared to EGCwould firms). The results for AVAR also show a slight reduction in abnormal volatility, although it is not statistically significant. This suggests that EGC firms tend to exhibit lower information content of earnings after the Act.[25] Panel B of Table 2.4 reports the estimation of equations (5) and (6) for the restricted sample of FULLDISC firms. The results show that earnings are

[25] This result is further supported in section 5.3 where I analyze alternative hypotheses related to firm age and profitability as potential drivers of the observed differences in AVOL and AVAR. I perform a matching strategy which shows that EGC firms have significantly lower AVOL and AVAR relative to similar (on observables) EGCwould firms, controlling for all controls and industry and year fixed effects.

significantly more informative after the JOBS Act for FULLDISC firms: the estimated coefficient of POST is positive and statistically significant in all four specifications. I further elaborate on this unexpected finding in Section 6, where I examine the potential mechanisms that could explain the decline (increase) in the information content of earnings for EGC (FULLDISC) firms.

2.6.2 The JOBS Act disclosure provisions

If the reduced disclosure provisions are behind the observed reduction in information content for firms that implement the exemptions, I expect that a higher use of these exemptions will be associated with a larger reduction in the information content of earnings. Therefore, I collect information on which exemptions each EGC has been applying during the years after the IPO. To extract this information, I parse all 10-Ks and DEF 14A filings.[26] In particular, I look for standardized keywords or short sentences that firms use when expressing their use (or not use) of an exemption. Finally, manual inspection of the filings is performed from the EDGAR website when needed.

Table 2.5 presents some basic descriptive statistics on the use of the disclosure provisions. After the Act, 447 unique firms filed as an EGC (which yields a total of 816 firm-year observations). Untabulated statistics show that EGC firms represented 75.3% of the IPOs in 2012, increasing to 87.7% in 2015.[27] Furthermore, I observe that 94 firms lose their EGC status mainly because they breach the $700 million public float threshold (i.e. they become a large accelerated filer).

Table 2.5 provides further information on the usage of disclosure provisions, reporting that a 97.4% of the annual reports (795 out of 816) do not include an audit attestation of internal controls, while 78.1% use the reduced disclosure on executive compensation and 67.0% do not provide the CD&A section. [28] Also, it seems that EGC

[26] I employ R (Edgar package) and a Python script for such analysis.

[27] Descriptive statistics on EGC disclosure provisions are based on information extracted from all parsed documents, irrespective of whether they have complete observations (i.e. non-missing values) in the other variables used in the study. The reason is that some control variables (e.g. having a big 4 auditor) may show a missing value in a given year, causing an EGC firm to drop in that particular year and appearing in the next one (provided all control variables show valid observations). For consistency across years and because the goal in this section is to describe the application of the disclosure provisions, I use all parsed information. Statistics and conclusions do not differ significantly if I use, instead, only the observations with complete information.

[28] Very few EGC firms express their eligibility to be exempt from the mandatory audit firm rotation provision. At the time of writing the JOBS Act, and in an attempt to boost auditor independence, the PCAOB was considering imposing auditor term limits on public companies. It is likely that, based on this expectation, the SEC incorporated this regulation in the JOBS Act before the audit regulation was made

firms generally choose to comply with new or revised accounting standards (although a substantial amount of reports, 297 out of 816, do not mention such provision) and with the non-binding advisory shareholder vote on executive compensations (only in 5.1% of the observations this provision is elected). The last two columns of Table 2.5 show whether EGC firms are being consistent in the provisions they apply. The data suggest that provision usage is sticky: out of 447 EGC firms, only 5 switch from not including the audit attestation of internal controls to including it (or vice versa) and only 16 change their usage of the CD&A provision.

I hypothesized that EGC firms which apply more disclosure provisions should experience a more severe decline in the information content of earnings. For that purpose, I split my main variable EGC into two new indicator variables: EGC_{Low} (which equals 1 for an EGC firm that uses three or fewer disclosure provisions in its annual filings, and 0 for FULLDISC firms) and EGC_{High} (which equals 1 for EGC firms that use four or five disclosure provisions). I establish three provisions as the cutoff to be considered a "high provision user" because, as observed in Table 2.5, most EGCs apply three provisions (i.e. audit attestation of internal controls, the reduced disclosure on executive compensation and not providing the CD&A section). I then reestimate equations (3) and (4) using these two indicator variables instead of EGC. Given the stickiness in the usage of disclosure provisions, I also provide pooled OLS specifications.

The estimated coefficients of these regressions are shown in Table 2.6. The results show that, relative to FULLDISC firms, EGC firms which use more disclosure provisions have less informative earnings than EGC firms which use fewer provisions (i.e. across all specifications and samples the estimated coefficients of EGC_{High} are negative and statistically significant and of a larger magnitude than the estimated coefficients of EGC_{Low}). I test whether this difference in the estimated coefficients between EGC_{Low} and EGC_{High} is statistically significant (bottom row of the table). The results suggest that the difference in information content are statistically significant in the pooled specifications (columns (1), (2), (5) and (6) but not when firm fixed effects are included. This was expected given that in Table 2.5 I showed evidence of very low within-firm variation in the number of provisions applied over time (only 46 firms switch the use of provisions). Thus, when firm fixed effects are included, most of the

effective. The PCAOB eventually abandoned the project and that may be the reason why very few EGCs mention this provision in their annual filings. Therefore, I do not include this provision in my analysis.

variation in provision usage is eliminated, leading to coefficient estimates which, though still significant and suggestive of the increased effect of high provision usage, have relatively high standard errors. Overall, I believe these results provide partial support to the argument that the scaled down disclosure, and in particular, the extreme use of the JOBS Act provisions, produce less informative earnings for EGC firms.

2.6.3 Alternative arguments: Firm size, age and profitability

In light of the main result in Table 2.3, one may be concerned about alternative explanations behind the observed result. In this subsection, I look at three potential confounding variables that may drive the main finding, namely, size, profitability and age.

It may be argued that size, and not the reduced disclosure, may be behind the difference I observe in the information content of earnings between EGC and FULLDISC firms. That is, smaller firms may have less informative earnings to begin with (since they receive less investor attention in the days surrounding the earnings announcement event). I provide three arguments to rule out this alternative hypothesis. First, all model specifications include the market value of equity as a control for size (and most of them also include firm fixed effects), absorbing the potential omitted correlation between size and the dependent variables. Second, size differences, if relevant, should also be apparent in the pre-JOBS Act period between NEGCwould (large) and EGCwould (smaller) firms. Results in Panel A of Table 2.3 show that this is not the case. Finally, I provide an additional test which looks at whether the information content of earnings for EGC firms in the post-JOBS Act period differs from that of EGCwould firms. EGCwould firms are similar to EGC in that the two groups meet the requirements to be an EGC (in fact, EGC firms show a mean log market value of equity of 12.95, which is slightly larger that the mean value of 12.90 for EGCwould firms). If size were the source of the observed difference between EGC and FULLDISC firms after the Act, I should not observe significant differences between EGC and EGCwould firms in the post-Act period 2012-2015. Figure 2 provides some visual evidence by plotting the mean AVAR and AVOL for all firms that went for an IPO since 2002, distinguishing between EGC firms (subject to reduced disclosure), EGCwould firms

(full disclosure) and the rest of the non EGC firms (NEGC, full disclosure) in the post-Act period.[29]

Table 2.7 shows the result of this analysis. The models estimated in this table are similar to those in Panel B of Table 2.3, but instead I use now EGC as the baseline category. Thus, I include two dummies, one which identifies EGCwould companies and another which identifies the remaining NEGC firms. The results suggest that there are significant differences between EGC and EGCwould firms after the Act even if firm controls and firm fixed effects are added. All four specifications show a positive and statistically significant coefficient on EGCwould, suggesting that EGCwould firms have more informative earnings relative to EGC firms. If size was the driver of the reduced information content of earnings for EGC firms observed in Table 2.3, we should not observe such significant difference, given that both types of firms are similar in size by construction. Moreover, I find no significant differences between the estimated coefficients for EGCwould and NEGC, which are two groups of firms that are different in size but subject to the same disclosure requirements. The test of equality of coefficients ($\hat{\beta}_{\text{EGCwould}} = \hat{\beta}_{\text{NEGC}}$) fails to reject the null hypothesis that both coefficients are equal. Altogether, these results suggest that the significant difference in the information content of earnings announcement after the JOBS Act is not due to size differences.

Second, additionally to size, it may be argued that the type of firms that go public after the Act are different compared to the pre-Act period. For example, Dambra et al. (2015) document that firms with high proprietary costs (i.e. biotech and pharmaceuticals) increase IPO activity the most after the Act. It may be reasonable to think that a different type of firm is now accessing public markets and thus, EGC firms are fundamentally different from past IPO firms. In an attempt to mitigate this potential confounding effect, I test the main result in Table 2.3 by constructing a matched sample. In particular, I match EGC firms to similar (on observables) EGCwould firms using a logit propensity score that predicts the probability of being an EGC firm. The set of matching variables is consistent with those used in other JOBS Act studies and it includes measures of size (revenues and market value of equity), profitability (ROA and

[29] To achieve a robust estimate of the average AVOL and AVAR for EGCwould firms after the Act (2012-2015), I relaxed the 5 years condition to be an EGC firm. Relaxing this requirement does not affect the nature of the analysis, that is, the comparison between similar firms after the Act (EGC versus EGCwould). This results in averaging 151 EGCwould firms in the year 2015, instead of 37 observations if the 5 years requirement was applied.

LOSS_D), capital structure (LEV), big 4 audit (BIG4), an indicator variable for venture capital backed firms at the time of the IPO (VC_IPO) and firm age (AGE).[30] I use nearest neighbor matching without replacement to match EGCs after the Act with a single control EGCwould firm. I also require matching within industry, using the Fama-French 12 industry classification. This procedure mitigates the risk of observing a significant difference in the information content of earnings for reasons unrelated to the JOBS Act (e.g. differences in firm fundamentals). Panel A of Table 2.8 reports results from the matching procedure, which successfully matches 198 companies (no significant differences observed between groups). Panel B reports results of a regression of AVOL and AVAR on an EGC indicator variable that equals 1 for EGCs and 0 for their matched EGCwould firms. Firm fixed effects are not included, as no firm can switch from EGCwould to EGC firm (these are two separate entities). Thus, reported coefficients include industry and year fixed effects, all available control variables and standard errors clustered at firm and year-month level. Results are consistent with the main findings of the study. After controlling for potential observable confounding effects, EGC firms show less informative earnings than similar firms that went public before the JOBS Act, providing further support for the disclosure argumentation.

2.7 Mechanisms: Business press and analyst coverage

In this section, I examine two mechanisms that can help to explain the observed difference in the information content of earnings between EGC and FULLDISC firms: business press and analysts coverage.

First, I posit that business press can be used as an additional voluntary disclosure mechanism that further explains the decline in the information content of earnings for EGC firms. I argue that EGC firms compensate their reduced mandatory disclosure by concentrating more media attention in the days prior to the earnings announcements. In particular, I first examine whether more press items (i.e. full articles, news flashes, hot news flashes, tabular material and press releases) are available in the media for EGC firms after the Act. Untabulated results of estimation of equation (7) using ALLPRESS, ALLPRESS_EARN, ALLPRESS_REV, ALLPRESS_INSTRAD or ALLPRESS_TECHAN as dependent variables show no consistent statistical differences

[30] I obtain the age of the firm from the Field-Ritter dataset of company founding dates available at Jay Ritter's website (https://site.warrington.ufl.edu/ritter/files/2016/09/FoundingDates.pdf). Last accessed: September 2017. See, e.g., (Field and Karpoff 2002; Loughran and Ritter 2004)

in the number of press coverage items between EGCwould and NEGCwould firms or between EGC and FULLDSIC firms. I then concentrate on firm initiated press releases as a measure of voluntary disclosure. Panel A and B of Table 2.9 report the results of estimation of equation (7) using PRESS_REL, PRESS_REL_EARN and PRESS_REL_REV as the dependent variables. [31] Even if overall media coverage does not increase for EGC firms, I expect these firms to issue more press releases (i.e. voluntary disclosure) after the Act and hence compensate for their reduced mandatory disclosure. Column (1) of Panel A and B show that EGCwould firms (EGC firms) do not show a significantly higher number of press releases relative to NEGCwould (FULLDISC) before (after) the JOBS Act, although the estimates of the post-JOBS Act effects are all positive. However, when splitting the press releases by topic, I observe that EGC firms issue significantly more revenue-related press releases relative to FULLDISC firms after the Act (columns (3) and (6) of Panel B). This difference is statistically significant in both samples (t-stats of 2.15 and 2.72) and only after the Act.

This finding raises the question of why managers would want to eliminate previously mandated disclosure while at the same time increase voluntary disclosure. I argue that the costs of previous mandatory disclosure (e.g. potential internal control weaknesses or excessive executive compensation packages) may be well above the benefits of disclosure. In contrast, the cost of releasing information through the media is much lower (e.g. press release). Additionally, this information is more flexible in both format and content and can be timed to the firm's advantage. For example, it has been shown that business press items help reduce information asymmetries (Bushee et al. 2010) and cost of capital (Kothari et al. 2009). In this study, the fact that managers disclose more revenue-related press releases might be an attempt to disclose good yearly sales volumes. Taken together, these results suggest that EGC firms release more voluntary revenue-related information after the Act, information that may already be impounded into the stock price, weakening the market reaction for EGC firms when the earnings announcement event takes place. Given the evidence shown in Table 2.6, I interpret this negative effect on the information content of earnings of voluntary disclosure as incremental to the main disclosure deregulation effect.

The second mechanism I explore is analyst coverage. Prior literature has shown evidence of a positive association between the number of analysts following and the

[31] The analysis on press releases does not include insider trading and technical analysis topics because no press releases were issued on such topics.

information content of earnings (DeFond et al. 2007; Landsman et al. 2012). This association may help to explain the higher (lower) informative earnings observed for FULLDISC (EGC) firms in previous sections. I first check for differences between EGC and FULLDISC firms regarding analyst coverage. I estimate regressions similar to equation (7) but with the three traditional measures of analyst coverage as dependent variables (UE, DISP and NUMEST). Panel A and B of Table 2.10 report that there is one variable which is significantly different across all specifications (full and post crisis sample), namely the number of analysts following the firm (NUMEST, see columns (3) and (6)), both before (Panel A) and after the Act (Panel B). The negative and significant coefficients in columns (3) and (6) suggest that fewer analysts follow EGCwould and EGC firms relative to NEGCwould and FULLDISC firms. This is consistent with more analysts generally following bigger firms. However, coefficients are larger in Panel B (-2.857 and -2.229), suggesting that the difference in analysts following is larger after the JOBS Act.

Next, I test whether this larger difference is driven by changes in analyst following of EGC or FULLDISC firms. Panel C of Table 2.10 shows the analysis for FULLDISC firms. In particular, the panel shows the result of regressing NUMEST on controls (excluding analyst related variables), firm and year fixed effects and the POST variable (equal to 1 for fiscal years in or after 2012). I find that after the Act there are between 1 and 2.5 more analysts following FULLDISC firms (t-statistics of 2.59 and 5.48 for the full and post crisis sample, respectively). This regression analysis cannot be replicated for EGC firms, since such firms only appear after 2012. However, tests can be constructed which compare the mean value of NUMEST for EGCwould firms (before the JOBS Act) and for EGC firms (after the Act). Untabulated results from both samples and from the matched sample described in section 5.3.2 report a decrease in analyst following. The estimated differences are -0.2 in the overall sample (p-values for a one-sided test of 0.08 in the full sample, and of 0.16 in the post crisis sample) and -1.5 for the matched sample (p-value of 0.02). Thus, the results suggest that there is a decrease in analyst following for EGC firms compared to the most comparable group of pre-JOBS Act EGC firms (i.e. matched sample of EGCwould).

This result may seem counterintuitive, since one might expect analysts to concentrate more on those firms with lower public disclosure (EGCs) and hence, provide investors with more valuable guidance. Nonetheless, economic reasoning would predict that investors who rely more on private information might now hold more

positions in EGC firms to benefit from profitable trades based on this private information (Ali et al. 2004; Bushee and Goodman 2007). To further understand analysts' incentives to follow more FULLDISC firms after the Act, I test whether institutional investors (with easier access to private information) increase their presence in EGC relative to EGCwould firms. Ackert and Athanassakos (2003) document a negative association between the presence of institutional investors and analysts following, possibly because there is no need of public information for institutional investors that acquire this information privately (through for example, closer contact with management). I obtain data from the "Institutional (13f) Holdings – s34" database, which provides information on the number of shares each institutional owner holds over the firm overall shares outstanding. I then create a variable, INSTOWN, which measures the percentage of institutional ownership for each firm. Untabulated t-tests suggest that more institutional investors are present in EGC firms after the Act relative to EGCwould firms, which is consistent with other studies on the JOBS Act (Barth, Landsman, and Taylor 2017).[32] I acknowledge that the mere presence of institutional ownership in EGC firms after the Act might not be uniquely due to an informational advantage of a reduced public disclosure. Some other factors could drive the attention of such investors to EGC firms (e.g. new corporate governance structures). Therefore, I interpret this result as tentative, but suggestive of a relationship which requires further research.

To sum up, my results suggest that more analysts follow FULLDISC firms after the Act and fewer analysts follow EGC firms, seemingly as a result of an increased presence of institutional owners (who rely more on private information) in EGC firms. This apparent relative shift in analyst coverage is in line with my finding of higher informative earnings of FULLDISC firms and lower informative earnings of EGC firms after the Act. Similar to Barth, Landsman, Raval, et al. (2017), I argue that investors of firms with more analysts following may be able to interpret the valuation implications of the announced earnings more quickly and therefore, react quicker (stronger market reaction) to the announcement event.

[32] Untabulated regressions using the post crisis sample and including all control variables, firm and year fixed effects also provide evidence of an increase in institutional ownership in EGC firms after the Act.

2.8 Conclusions

This study examines whether a major disclosure deregulation, the JOBS Act, had any effect on the informativeness of accounting information in newly public firms. I predict and find a significant difference in the information content of earnings of EGC firms, for which the JOBS Act allowed a reduced disclosure, relative to full disclosure firms after the JOBS Act. I provide two main sets of results. First, I show evidence of a decline in the information content of earnings of EGC firms after using the Act's disclosure provisions. I provide evidence that disclosure is behind this effect, since firms that make further use of the disclosure exemptions show a greater reduction in the information content of earnings. I also find that EGC firms seem to substitute their reduced mandatory disclosure with more voluntary disclosure. Specifically, after the Act, EGC firms issue more revenue-related press releases in the days preceding the earnings announcement event. This new information may already be impounded into stock prices by the day of the announcement and, together with the reduced disclosure effect, produces less informative earnings in EGC firms. Second, I document an unexpected increase in the information content of earnings of FULLDISC firms. This finding is unexpected since, all else equal, these firms continue to disclose the same information after the JOBS Act. I interpret this finding as providing evidence of a spillover effect which results from the deregulation event. In particular, I argue that the Act may have incentivized more analysts to follow FULLDISC firms and fewer analysts to follow EGC firms, thus increasing the information content of earnings for the former and decreasing it for the latter. I show evidence of these two effects. To the best of my knowledge, this study provides the first empirical evidence that disclosure deregulation events have a negative effect on the information content of earnings in the firms affected by the deregulation and, moreover, that disclosure deregulation may generate spillover effects in firms not intended to be affected by the regulation.

Table 2.1. JOBS Act provisions applicable to EGC firms in the first five years after the IPO registration statement

Provision	Pre-JOBS Act (also applicable to post-JOBS Act non-EGC)	Post-JOBS Act (applicable to EGC companies)
1. Compliance with Section 404(b) of SOX by which auditors attest the effectiveness of internal control systems	Beginning with the second 10-K after the IPO registration statement	Exempt
2. Adoption of new or revised accounting standards	Applicable when effective for public firms	Delay application until it applies to private firms
3. Independent auditors adoption of new audit requirements and audit firm rotation dictated by the Public Company Accounting Oversight Board (PCAOB)	Applicable	Exempt
4. Reduced executive compensation disclosures in proxy statements (form DEF 14A) or annual reports (10-Ks)	Required full disclosure	Compensation for a minimum of three (rather than five) named executives and no CD&A section required
5. Dodd-Frank Act: Non-binding advisory say-on pay votes (Say on Pay, Say on Frequency and Say on Golden Parachute)	Applicable	Exempt from compensation voting requirements

Note: EGC companies will also benefit from "Pay versus performance" and "CEO pay-ratio rules" disclosure exemptions. These rules are either applicable in fiscal years beginning on 2017 ("CEO pay-ratio") or do not have a beginning reporting period yet ("Pay versus performance")

Table 2.2. Descriptive statistics

Panel A. Full sample (IPOs since January 2002)

Variable	N	Mean	Std.dev	p25	p50	p75
EGC / EGCwould	5,650	0.42	0.49	0.00	0.00	1.00
AVOL	5,650	1.95	1.43	1.04	1.60	2.41
AVAR	5,650	5.92	10.33	0.72	2.23	6.33
SIZE	5,650	13.56	1.59	12.61	13.42	14.36
REPLAG	5,650	50.89	15.99	40.00	51.00	59.00
LEV	5,650	0.51	0.30	0.29	0.49	0.69
LOSS_D	5,650	0.36	0.48	0.00	0.00	1.00
ROA	5,650	-0.05	0.30	-0.06	0.02	0.07
BIG4	5,650	0.88	0.33	1.00	1.00	1.00
UE	5,650	0.02	0.15	0.00	0.00	0.01
DISP	5,650	0.01	0.05	0.00	0.00	0.01
NUMEST	5,650	8.10	5.45	4.00	7.00	10.00
ALLPRESS	4,456	224.48	599.31	95.00	146.00	229.00
ALLPRESS_EARN	4,456	5.60	3.19	4.00	5.00	7.00
ALLPRESS_REV	4,456	2.61	3.38	1.00	2.00	3.00
ALLPRESS_INSTRAD	4,456	17.61	27.32	2.00	9.00	22.00
ALLPRESS_TECHAN	4,456	6.26	11.18	0.00	0.00	0.00
PRESS_REL	4,456	34.78	268.62	12.00	18.00	27.00
PRESS_REL_EARN	4,456	1.74	1.11	1.00	1.00	3.00
PRESS_REL_REV	4,456	0.19	0.80	0.00	0.00	0.00
INSTOWN	4,171	0.67	0.40	0.45	0.70	0.88

Panel B. Post crisis sample (IPOs since July 2009)

Variable	N	Mean	Std.dev	p25	p50	p75
EGC / EGCwould	1,830	0.41	0.49	0.00	0.00	1.00
AVOL	1,830	1.95	1.47	1.02	1.56	2.43
AVAR	1,830	6.23	10.89	0.82	2.34	6.52
SIZE	1,830	13.61	1.34	12.67	13.53	14.45
REPLAG	1,830	53.00	16.38	41.00	54.00	62.00
LEV	1,830	0.52	0.33	0.28	0.48	0.72
LOSS_D	1,830	0.46	0.50	0.00	0.00	1.00
ROA	1,830	-0.09	0.32	-0.16	0.01	0.05
BIG4	1,830	0.87	0.34	1.00	1.00	1.00
UE	1,830	0.02	0.11	0.00	0.00	0.01
DISP	1,830	0.01	0.07	0.00	0.00	0.01
NUMEST	1,830	7.90	5.37	4.00	6.00	9.00
ALLPRESS	1,009	282.31	1,134.56	100.00	152.00	233.00
ALLPRESS_EARN	1,009	5.70	3.34	4.00	5.00	7.00
ALLPRESS_REV	1,009	2.26	2.13	1.00	2.00	3.00
ALLPRESS_INSTRAD	1,009	19.02	25.70	3.00	10.00	24.00
ALLPRESS_TECHAN	1,009	2.69	7.68	0.00	0.00	0.00
PRESS_REL	1,009	67.84	560.72	12.00	17.00	24.00
PRESS_REL_EARN	1,009	1.81	1.05	1.00	2.00	3.00
PRESS_REL_REV	1,009	0.11	0.50	0.00	0.00	0.00
INSTOWN	885	0.65	0.28	0.43	0.68	0.86

Panel A and Panel B present descriptive statistics for the full and post crisis sample respectively. Appendix A defines all variables and their computations.

Table 2.3. Effect of the JOBS Act on the information content of earnings

Panel A. Pre-JOBS Act sample (fiscal years 2002-2011)

	IPOs since 2002		IPOs since July 2009	
	(1)	(2)	(3)	(4)
	AVOL	AVAR	AVOL	AVAR
EGCwould	-0.102	-0.485	-0.371	-0.633
	(-1.15)	(-0.68)	(-0.84)	(-0.29)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.042	0.035	0.318	0.148
Obs.	2,970	2,970	239	239

Panel B. Post-JOBS Act sample (fiscal years 2012-2015)

	IPOs since 2002		IPOs since July 2009	
	(1)	(2)	(3)	(4)
	AVOL	AVAR	AVOL	AVAR
EGC	-0.544***	-2.418*	-0.477***	-1.951*
	(-4.34)	(-1.94)	(-3.70)	(-1.71)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.021	0.013	0.024	0.016
Obs.	2,680	2,680	1,598	1,598

This table reports the results of estimating equations (3) and (4) for IPOs issued since January 2002 (columns (1) and (2)) and July 2009 (columns (3) and (4)) to the end of 2015. Panel A summarizes results for fiscal years prior to the JOBS Act (i.e. 2002-2011). EGCwould is an indicator variable that equals 1 for firms that would have been EGC status firms had the Act been approved before their IPO (and 0 for NEGCwould firms). Panel B summarizes the post-JOBS Act sample (fiscal years 2012-2015), with EGC being a 1 for EGC status firms and 0 for FULLDISC firms (i.e. NEGCwould, EGCwould firm-year observations in or after 2012 and new IPOs that are non EGC). All specifications include firm and year fixed effects, time variant control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. See Table 2.A1 for variable descriptions.

Table 2.4. Source of the difference in the information content of earnings after the Act

Panel A. The information content of earnings before (EGCwould) and after (EGC firms) the JOBS Act

	IPOs since 2002			IPOs since 2009		
	EGCwould	EGC	p-value	EGCwould	EGC	p-value
AVOL	1.778	1.625	0.013**	1.848	1.625	0.032**
AVAR	4.091	4.219	0.668	4.299	4.219	0.910
Obs.	2,602	816		267	816	

Panel B. The information content of earnings before and after the JOBS Act for FULLDISC firms

	IPOs since 2002		IPOs since 2009	
	(1)	(2)	(3)	(4)
	AVOL	AVAR	AVOL	AVAR
POST	0.130*	3.016***	0.433**	6.054***
	(1.69)	(4.03)	(2.25)	(5.37)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	N	N	N	N
R^2	0.015	0.026	0.024	0.035
Obs.	3,304	3,304	1,092	1,092

This table reports results regarding the analysis of the group of firms that originate the difference in the information content of earnings after the JOBS Act. Panel A shows univariate t-tests of AVOL and AVAR for EGCwould (before the Act) and EGC (after the Act) for the full and post crisis sample. Panel B reports results from equations (5) and (6), where POST is an indicator variable equal to 1 in fiscal years 2012 to 2015 and 0 otherwise. All specifications include firm fixed effects, time variant control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. See Table 2.A1 for variable descriptions. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.5. JOBS Act disclosure provisions

Provision	EGC firm-year using the provision	EGC firm-year not using the provision	EGC firm-year not mentioning the use of the provision	% use	Firms that do not switch from using to not using provision (or vice versa) during EGC status	Firms that switch from using to not using provision (or vice versa) during EGC status
No audit attestation of Internal Controls	795	6	15	*97,4%*	442	5
Delay new or revised accounting standards	16	503	297	*2,0%*	447	0
No disclosure of the CD&A section	547	184	85	*67,0%*	431	16
No non-binding advisory vote on executive compensation	42	689	85	*5,1%*	447	0
3 rather than 5 named executives	637	95	84	*78,1%*	422	25

This table presents descriptive statistics regarding the usage of disclosure provisions allowed by the JOBS Act. The first column lists the five provisions eligible for EGC firms. The following three columns document whether the firms use, not use or do not mention the usage of each provision in any given fiscal year. In total, I parse 816 filings filed as an EGC between fiscal years 2012 and 2015. These filings have been filed by 447 unique firms, out of which a vast majority (penultimate column) never switches from using to not using a provision (or vice versa), that is, the decision to apply a provision or not is really sticky over time.

Table 2.6. Effect of disclosure provisions on the information content of earnings announcements

	IPOs since 2002				IPOs since July 2009			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AVOL	AVAR	AVOL	AVAR	AVOL	AVAR	AVOL	AVAR
EGC_{Low}	-0.196*	-1.266	-0.515***	-2.332*	-0.214*	-1.227	-0.446***	-1.886*
	(-1.88)	(-1.58)	(-4.15)	(-1.89)	(-1.81)	(-1.25)	(-3.48)	(-1.66)
EGC_{High}	-0.451***	-5.314***	-1.598*	-5.504**	-0.448***	-5.191***	-1.513*	-4.191
	(-3.95)	(-5.88)	(-1.90)	(-2.03)	(-3.48)	(-4.57)	(-1.82)	(-1.60)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	N	Y	Y	N	N	Y	Y
Industry FE	Y	Y	N	N	Y	Y	N	N
Adj. and Within R^2	0.135	0.077	0.017	0.007	0.137	0.075	0.024	0.013
Obs.	2,680	2,680	2,680	2,680	1,598	1,598	1,598	1,598
T-test of diff. in coeff. ($\hat{\beta}_{EGCLow} > \hat{\beta}_{EGCHigh}$)	*0.016*	*0.000*	*0.105*	*0.109*	*0.033*	*0.001*	*0.107*	*0.179*

This table reports the effect of the JOBS Act disclosure provisions (i.e. high versus low usage) on the information content of earnings after the JOBS Act (i.e. years 2012-2015). Specifically, the estimated equation for AVOL and AVAR (DV) is: $DV_{it} = \beta_0 + \beta_1 \text{EGCLow}_{it} + \beta_2 \text{EGCHigh}_{it} + \sum_k \beta_k \text{Controls}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$, where EGC_{Low} is an indicator variable that equals 1 for EGC firm-year observations that use 3 or less provisions (and 0 for FULLDISC firms), EGC_{High} equals 1 for EGC firm-year observations with 4 or 5 disclosure provisions (and 0 for FULLDISC firms). All specifications include all control variables as described in Appendix A, year fixed effects (α_i) and two-way clustering of standard errors at firm and year-month level. Pooled specifications are shown in columns (1), (2), (5) and (6) (including industry fixed effects) and firm fixed effects specifications are reported in columns (3), (4), (7) and (8). A one-tailed test of difference in coefficients is also presented. T-statistics are displayed in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.7. Testing the effect of firm size on the information content of earnings

	IPOs since 2002		IPOs since July 2009	
	(1)	(2)	(3)	(4)
	AVOL	AVAR	AVOL	AVAR
EGCwould	0.471**	4.716*	0.737**	4.836*
	(2.08)	(1.87)	(2.65)	(1.67)
NEGC	0.530***	2.324*	0.413***	1.768*
	(4.08)	(1.95)	(3.17)	(1.67)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.021	0.015	0.025	0.019
Obs.	2,680	2,680	1,598	1,598
T-test of diff. in coeff. ($\hat{\beta}_{\text{EGCwould}} = \hat{\beta}_{\text{NEGC}}$)	*0.756*	*0.258*	*0.183*	*0.265*

This table reports an augmented version of equations (3) and (4). The estimated augmented equation for any of the two dependent variables (DV) is: $DV_{it} = \beta_0 + \beta_1 \text{EGCwould}_{it} + \beta_2 \text{NEGC}_{it} + \sum_k \beta_k \text{Controls}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$, where EGCwould takes the value of 0 for EGC companies (reference category) and 1 for EGCwould. NEGC takes the value of 0 for EGC firms and 1 for non EGC firm-year observations (i.e. NEGCwould and IPOs that are non EGC after the Act). Figure 2 illustrates this variable construction. Note that only the post-JOBS Act regression is presented (2012-2015 fiscal years period) as no EGC variable can exist in the pre-JOBS Act period. All specifications include firm and year fixed effects, time variant control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. See Table 2.A1 for variable descriptions.

Table 2.8. Propensity Score Matching results

Panel A. Results from the matching procedure

Variable	EGCwould (pre-Act)		EGC (post-Act)		p value
	N	Average	N	Average	
Revenues	198	140.08	198	163.23	0.23
Market Value of Equity	198	13.08	198	13.16	0.54
LOSS_D	198	0.67	198	0.63	0.40
LEV	198	0.38	198	0.36	0.62
ROA	198	-0.17	198	-0.13	0.16
BIG4	198	0.84	198	0.88	0.25
AGE	198	2.17	198	2.27	0.19
VC_IPO	198	0.63	198	0.59	0.36

Panel B. Matched sample: The effect of the JOBS Act on the information content of earnings announcements

	IPOs since 2002		IPOs since 2009	
	(1)	(2)	(3)	(4)
	AVOL	AVAR	AVOL	AVAR
EGC	-0.193*	-2.688***	-0.221	-3.020**
	(-1.79)	(-3.25)	(-1.18)	(-2.42)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adjusted R^2	0.097	0.091	0.107	0.080
Obs.	1,531	1,531	643	643

Panel A reports results on the matching procedure between EGCwould and EGC firms, resulting in 198 matched companies. Panel B reports the result of a regression of AVOL and AVAR on an indicator variable, EGC, that equals 1 for matched EGCs and 0 for matched EGCwould firms. Reported specifications include industry and year fixed effects, all available control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. See Table 2.A1 for variable descriptions.

Table 2.9. Business press coverage before and after the Act

Panel A. Press releases before the JOBS Act (fiscal years 2002-2011)

	IPOs since 2002			IPOs since 2009		
	(1)	(2)	(3)	(4)	(5)	(6)
	PRESS_REL	PRESS_REL_ EARN	PRESS_REL_ REV	PRESS_REL	PRESS_REL_ EARN	PRESS_REL_ REV
EGCwould	-1.112	0.052	-0.064	-3.358	-0.088	-0.038
	(-1.21)	(0.64)	(-1.10)	(-1.09)	(-0.27)	(-0.48)
Controls / Firm FE / Year FE	Y	Y	Y	Y	Y	Y
R^2	0.073	0.027	0.008	0.186	0.178	0.036
Obs.	2,638	2,638	2,638	207	207	207

Panel B. Press releases after the JOBS Act (fiscal years 2012-2015)

	IPOs since 2002			IPOs since 2009		
	(1)	(2)	(3)	(4)	(5)	(6)
	PRESS_REL	PRESS_REL_ EARN	PRESS_REL_ REV	PRESS_REL	PRESS_REL_ EARN	PRESS_REL_ REV
EGC	12.872	0.303	0.182**	23.320	0.336	0.242***
	(1.13)	(1.49)	(2.15)	(1.18)	(1.57)	(2.72)
Controls / Firm FE / Year FE	Y	Y	Y	Y	Y	Y
R^2	0.042	0.021	0.008	0.075	0.039	0.029
Obs.	1,818	1,818	1,818	809	809	809

Table 2.9 reports results from equation (7). Dependent variables terminated in "EARN" and "REV" mean press pieces with an earnings and revenue-related topic, respectively. Panel A uses press releases as dependent variables in the pre-Act period. EGCwould is an indicator variable that equals 1 for EGCwould firms and 0 for NEGCwould firms. Panel B uses press releases as dependent variables in the post-Act period, with EGC=1 for EGC firms and 0 for FULLDISC firms. All specifications include firm and year fixed effects, time variant control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. See Table 2.A1 for variable descriptions.

Table 2.10. Analyst coverage before and after the Act

Panel A. Pre-JOBS Act sample (fiscal years 2002-2011)

	IPOs since 2002			IPOs since 2009		
	(1)	(2)	(3)	(4)	(5)	(6)
	UE	DISP	NUMEST	UE	DISP	NUMEST
EGCwould	-0.012**	-0.002**	-1.714***	-0.020	-0.004	-1.929**
	(-2.24)	(-2.10)	(-5.54)	(-0.99)	(-0.68)	(-2.79)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
R^2	0.043	0.094	0.264	0.196	0.129	0.477
Obs.	2,970	2,970	2,970	239	239	239

Panel B. Post-JOBS Act sample (fiscal years 2012-2015)

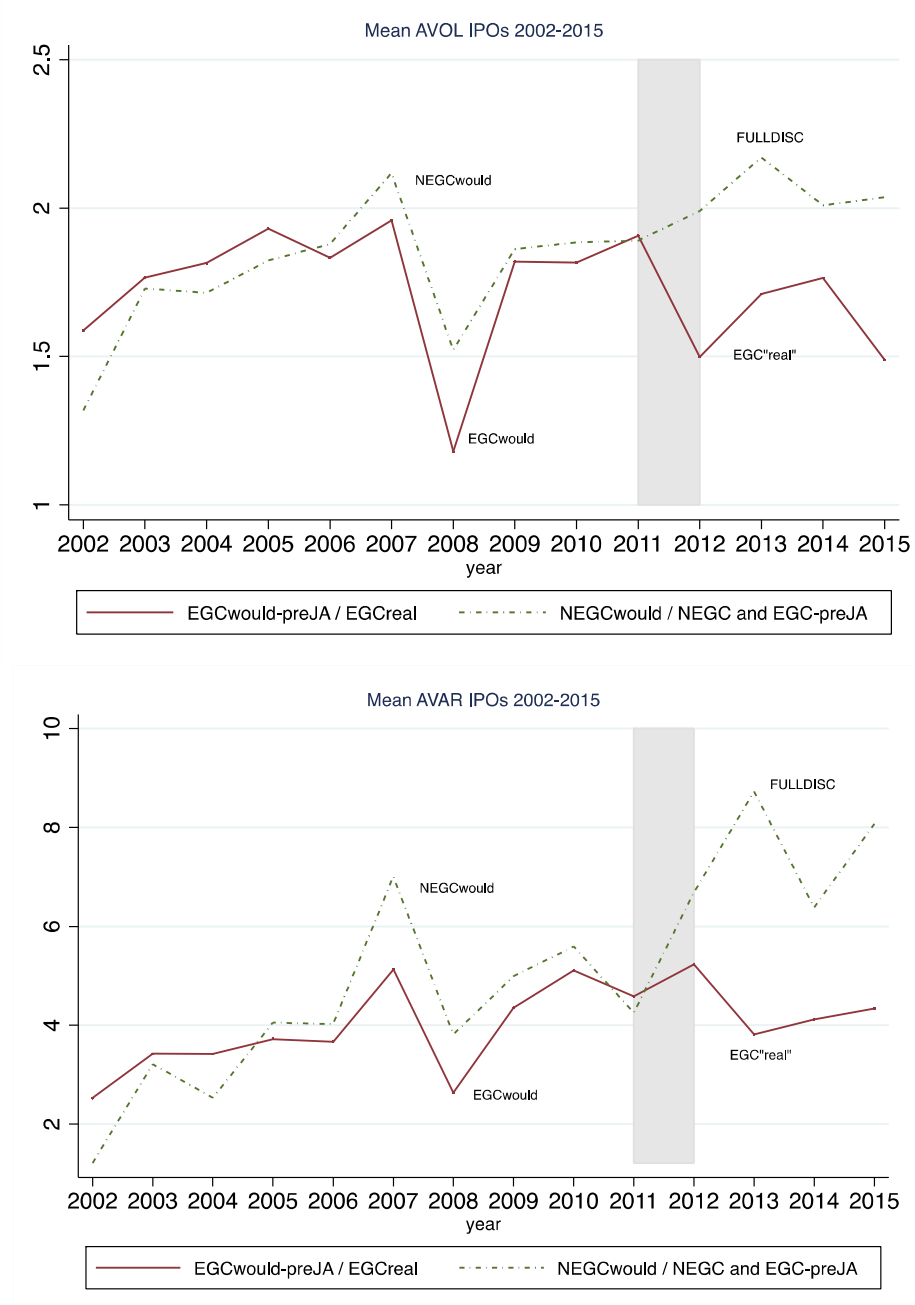
	IPOs since 2002			IPOs since 2009		
	(1)	(2)	(3)	(4)	(5)	(6)
	UE	DISP	NUMEST	UE	DISP	NUMEST
EGC	0.008	-0.001	-2.857***	0.001	-0.001	-2.229***
	(1.48)	(-0.65)	(-5.10)	(0.34)	(-0.49)	(-3.86)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
R^2	0.033	0.087	0.125	0.049	0.016	0.204
Obs.	2,680	2,680	2,680	1,598	1,598	1,598

Panel C. NUMEST for FULLDISC firms in the pre (2002-2011) versus post-Act (2012-2015) period

	IPOs since 2002	IPOs since 2009
	(1)	(2)
	NUMEST	NUMEST
POST	0.972**	2.538***
	(2.59)	(5.48)
Controls	Y	Y
Firm FE	Y	Y
R^2	0.146	0.128
Obs.	3,304	1,092

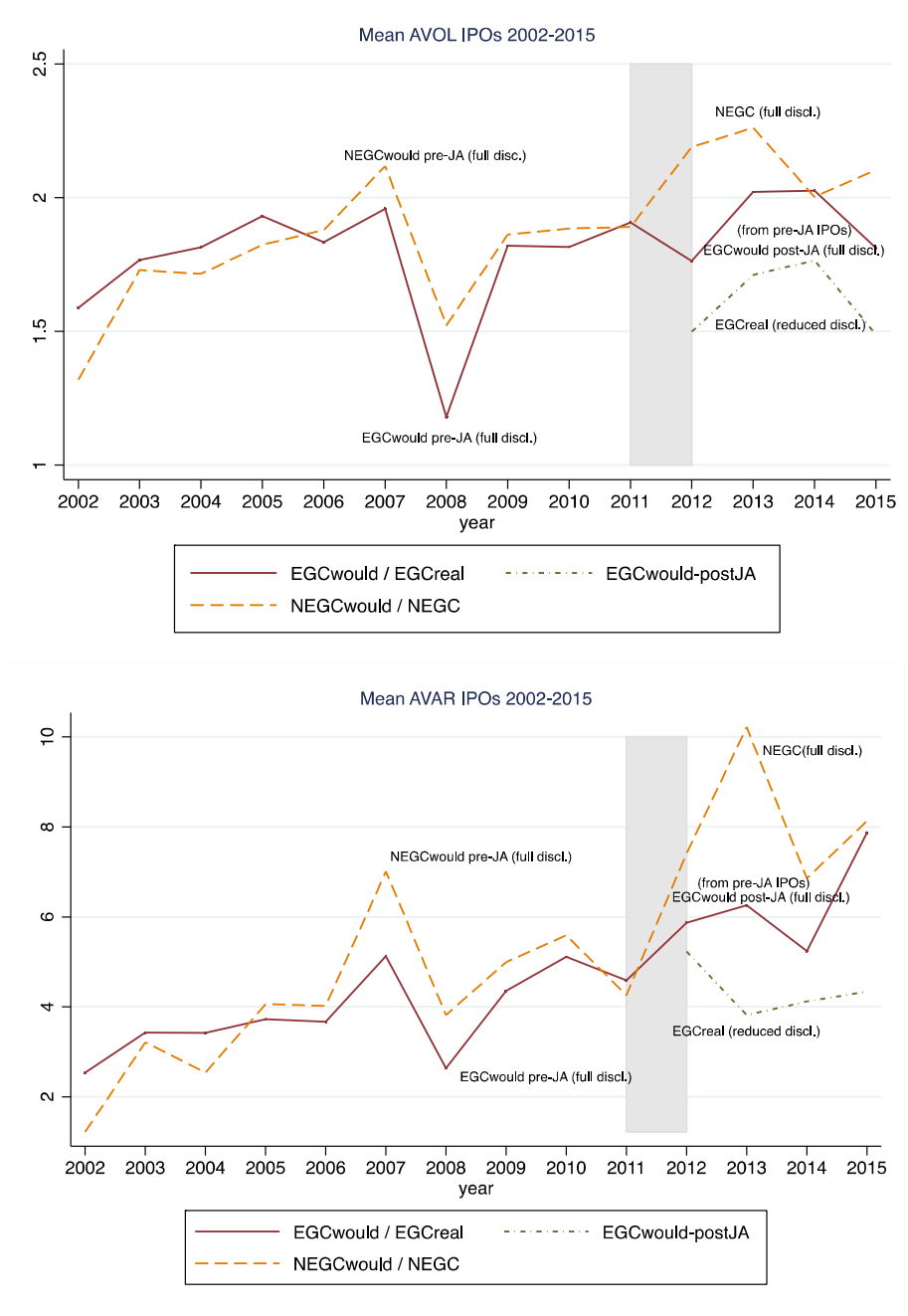
This table reports differences in analysts' forecasts variables before and after the JOBS Act. Panel A shows differences in analyst coverage dependent variables (UE, DISP and NUMEST) between EGCwould (1) and NEGCwould (0) before the Act. Likewise, Panel B reports differences between EGC (1) and FULLDISC (0) after the Act. Panel C reports changes in NUMEST for FULLDISC after the Act. POST is an indicator variable that equals 1 for fiscal years in or after 2012 (0 otherwise). Analysts control variables (i.e. UE, DISP and NUMEST) are omitted in all panels. All specifications include firm and year fixed effects, time variant control variables and two-way clustering of standard errors at firm and year-month level. T-statistics are displayed in parenthesis. See Table 2.A1 for variable descriptions. * p<0.10, ** p<0.05, *** p<0.01.

Figure 2.1. Evolution of AVOL and AVAR



This figure presents the evolution of Abnormal Volume (AVOL) and Abnormal Volatility (AVAR) for firms that went public in or after 2002. The dotted line shows the unconditional mean of AVOL and AVAR for firms that would have been non EGC prior to the Act and are FULLDISC after it (i.e. NEGCwould, EGCwould firm-year observations in or after 2012 and new IPOs that are non EGC). The solid line depicts firms that would have been EGC had the JOBS Act been implemented before their IPOs (i.e. EGCwould) and "real" EGC firms after the Act (i.e. reduced disclosure allowed).

Figure 2.2. Evolution of AVOL and AVAR



This figure presents the evolution of Abnormal Volume (AVOL) and Abnormal Volatility (AVAR) for firms that went public in or after 2002. The dashed line shows the unconditional mean of AVOL and AVAR for firms that would have been NEGC prior to the Act and NEGC after it (full disclosure is required over the entire period). The solid line depicts firms that would have been EGC had the JOBS Act been implemented before their IPOs (full disclosure is required over the entire period). The dotted line summarizes the "real" EGC status firms that filed after the Act (reduced disclosure allowed).

2.9 Supplementary appendix

Table 2.A1. Variable definitions and sources

Main variables	Description
AVOL	Abnormal trading volume; average daily trading volume during firm's earnings announcement window [-1,0,1] scaled by the average trading volume during the non-event period [-120 to -21, +21 to +120]. AVOL is winsorized at a 1% and 99% in all analysis. Source: CRSP.
AVAR	Abnormal return volatility; average stock return volatility during firm's earnings announcement window [-1,0,1] scaled by the firm's stock return volatility over the non-event period. AVAR is winsorized at a 1% and 99% in all analysis. Source: CRSP.
EGC	1 = Firm is an EGC (post-Act) or EGCwould (pre-Act); 0 = Firm is FULLDISC (full disclosure post-Act, i.e. NEGCwould, EGCwould firm-year observations in or after 2012 and new IPOs that are non EGC post-Act) or NEGCwould (full disclosure pre-Act).
POST	1 = Fiscal years between 2012 and 2015; 0 = Fiscal years between 2002-2011
ALLPRESS	Number of press items (i.e. full articles, news flashes, hot news flashes, press releases and tabular material) published in the days [-2,-180] before the announcement date. News topics include earnings (EARN), revenues (REV), insider trading (INSTRAD) and technical analysis (TECHAN). Source: Ravenpack Dow Jones Edition
PRESS_REL	Number of press releases published in the news in the days [-2,-180] before the announcement date. Press releases topics include earnings (EARN), revenues (REV), insider trading (INSTRAD) and technical analysis (TECHAN). Source: Ravenpack Dow Jones Edition
Control variables	
SIZE	Natural logarithm of market value of equity (share price x number of shares outstanding) at fiscal year end. Source: CRSP.
REPLAG	Number of days between firm's fiscal year end (datadate) to the earnings announcement day (rdq). Source: Compustat quarterly.
LEV	Firm's total liabilities scaled by total assets at fiscal year-end. Source: Compustat Annual.
LOSS_D	1 = Negative Earnings Per Share; 0 = Otherwise. Source: Compustat Annual
ROA	Net income scaled by total assets. Source: Compustat Annual
BIG4	1 = Firm is audited by a big 4 audit company; 0 = Otherwise. Source: Compustat Annual
UE	Absolute difference between actual EPS and the most recent (to the earnings announcement date) mean analyst estimate of EPS, divided by the closing stock price on the earnings announcement date. Source: I/B/E/S Unadjusted Summary file and Unadjusted Actual file
DISP	Standard deviation of analysts' EPS estimates divided by the closing stock price on the earnings announcement date. Source: I/B/E/S Unadjusted Summary file
NUMEST	Number of analysts following in the most recent quarter prior to the earnings announcement date. Source: I/B/E/S Unadjusted Summary file
VC_IPO	1 = VC-backed at IPO; 0 = Otherwise. Source: SDC Platinum
AGE	Natural logarithm of firm age. Source: Field-Ritter dataset of company founding dates
INSTOWN	Percentage of shares outstanding owned by institutional investors. Source: 13f Holdings – s34

Chapter 3

3. Perceived personality traits, firm forecasts, and valuation

Joint with Antonio Davila

3.1. Introduction

Early stage equity investments play a fundamental role in providing capital to new ventures that typically are resource constrained with negative cash flows and limited access to traditional financing instruments. In these early stages, equity investors are especially important to trigger young firms' growth (Puri and Zarutskie 2012), innovation (Hall and Lerner 2010), and professionalization (Hellmann and Puri 2002). Yet, these investors face high uncertainty and conflicts due to information asymmetries that result in the associated need for ex-ante information, specific contract designs, and ex-post monitoring activities (Kaplan and Strömberg 2004). s

We focus on ex-ante information. Potential investors demand information to form their opinion about firm potential through several information channels. Two of them are especially relevant: financial projections and firm valuation (set by the entrepreneur), and entrepreneurs' presentations. Both pieces of information are a traditional first step for investors to decide whether to engage further with the firm (Huang and Pearce 2015; Kaplan and Strömberg 2004). However, evidence indicates that financial information included in the business plan is often biased because of

entrepreneurs' overconfidence and incentives to present a favorable portrait of the firm (Armstrong et al. 2007; Cassar 2010). This rather positive view of the firm can have relevant implications on early stage investors, which may forego specific deals because of, for example, inflated valuations (e.g. expected profitability targets are breached). We believe that it is in the interest of investors to anticipate such favorable reporting and therefore improve their information set for decision-making. We argue that investor perceptions of entrepreneurs' personality traits can be one channel through which investors can integrate entrepreneurs' behaviors and actions that speak about information reporting practices and the development of the firm more generally.

Our first research question examines the relationship between the ex-ante financial information that entrepreneurs make available to investors (i.e. financial forecast errors and proposed firm valuation) and entrepreneurs' perceived personality traits. Entrepreneurs' characteristics play a crucial role across all aspects of the firm, not only affecting the preparation and disclosure of information, but also shaping the development of the firm more generally. Thus, it is plausible that investors' perceptions of the entrepreneur are associated with actual firm outcomes. Prior research in traditional financing settings corroborates this argument. Huang and Pearce (2015) find an association between positive investors' perceptions of entrepreneurs and firm performance four years later. Duarte et al. (2012) use a peer-to-peer loan marketplace to document that higher perceptions of borrower trustworthiness correlate with better firm credit scores and lower default rates. In the same context, Ravina (2019) finds that perceived attractiveness in borrowers correlates with higher likelihood of receiving a loan and pay lower interests. Extending these findings to the early-stage equity financing context, our second research question examines the effect of investors' perceptions of entrepreneurs' personality traits on firm survival and actual investment decisions.

From a wide range of personality traits, we study those that prior literature has examined in relation to financing contexts, namely, passion, dominance, trustworthiness, competence, and attractiveness (Blankespoor et al. 2017; Brooks et al. 2014; Chen et al. 2009; Duarte et al. 2012; Ravina 2019). Borrowing from the social psychology and communication literatures, we use nonverbal communication to obtain our measures of perceived personality traits. Individuals form an impression of others not only through verbal information exchanges but also through a wealth of nonverbal cues like gestures, tone of voice, and facial expressions (Ambady et al.

2000; Rosenthal et al. 1979). These dynamic nonverbal cues transmit individual "expressive" information that becomes fundamental in forming subjective perceptions of others (Ambadar et al. 2005; Ambady and Rosenthal 1992). We therefore rely in nonverbal cues to obtain our measures of perceived personality traits.

Our sample includes 155 videos of entrepreneurs presenting their firms to an audience of about 100 investors between the years 2012 and 2015. First, we create a 40-second video out of each entrepreneur's presentation. Next, we mask the sound of each video, so that it is possible to hear the tone of voice but not its content. Thus, we capture a non-verbal behavioral realization of perceived personality traits that is independent of any content mentioned in the video such as growth prospects, strategic alliances, or past performance. We estimate investor perceptions of entrepreneurs' personality traits using an independent set of raters that view the 40-second videos of each presentation. We obtain ratings of each entrepreneur along the five personality dimensions using a seven-point Likert scale and average ratings from 1,772 unique respondents to construct our measures of entrepreneur's perceived personality traits.[33] Second, we obtain financial forecasts and firm valuations (set by the entrepreneurs) from a four-page document that each entrepreneur distributes to investors at the beginning of each investment forum. This document has different sections including strategy, marketing, or human resources among others.

We begin our analysis examining the relationship between entrepreneur's personality traits and firm revenue and earnings forecast errors. These financial forecasts capture whether the entrepreneur portrayed a more or less favorable projection of the firm, and allow us to establish associations with perceived individual traits. We find that presence (a component capturing passion, dominance, and openness in gestures) is positive and significantly associated with revenue and earnings forecast errors. We also find a positive association between perceived attractiveness and forecasting errors. Building from social psychology literature, we document that more passionate, dominant and attractive individuals show higher levels of confidence, which limit their search for information, hence biasing their expectations about the future (Cassar 2010; Kahneman and Lovallo 1993; Mobius and Rosenblat 2006). This narrow focus and omission of the broader picture consequently produces larger forecasting errors. The finding is also consistent with physiological

[33] We also rate entrepreneurs on openness in gestures to include a more direct measure of nonverbal display.

arguments: passionate and dominant individuals tend to hold greater levels of testosterone and cortisol, two hormones associated with risk taking and confident behaviors (Coates and Herbert 2008; Cueva et al. 2015; Jia et al. 2014).

Next, we explore the effect of personality traits on firms' valuations, survival, and investors' funding decisions. We find that entrepreneurs with higher presence are more likely to overvalue their firms and receive funding, but are less likely to survive. We argue that higher overconfidence and tolerance to risk drive high presence entrepreneurs to set higher valuations and engage in riskier behaviors (e.g. burn cash more rapidly), which in turn explains the lower rates of survival of their firms. Yet, investors are more likely to fund these high presence entrepreneurs. This finding is consistent with investors (and people more generally) attaching a set of positive qualities to passionate and dominant individuals, such as tenacity in pursuing goals, inspirational leadership, and dedication to the venture (Cardon et al. 2009; Chen et al. 2009; Mitteness et al. 2012). We also find attractive entrepreneurs to be positively associated with the likelihood of being funded, but not with survival or overvaluation. Prior literature finds that a physical attractive stereotype exists, by which people overestimate the qualities of attractive people regardless of whether they are more productive or better performers than less attractive people (Feingold 1992; Mobius and Rosenblat 2006; Ravina 2019). Overall, this stereotype argument is consistent with investors being more likely to fund more attractive individuals even though their firms do not survive longer.

This study contributes to several research streams. First, it speaks to how perceived personality traits shape management-reported information, which is an important vehicle for investors to decide where to invest, monitor firm activities, manage stakeholders conflicts, and exercise oversight (Bushman and Smith 2001). In our context, the role of financial projections and firm valuation can help to resolve potential agency conflicts. For instance, entrepreneur's projected performance can be used as a benchmark to set compensation and address entrepreneurs' moral hazard and rent-seeking behavior; alternatively, valuation information is relevant to define liquidation rights (Kaplan and Strömberg 2004). Overall, our study documents that certain perceived personality traits are associated with the entrepreneurs' information preparation process; traits that investors can take into account when hedging against potential agency conflicts and business model uncertainty.

Second, we contribute to the scarce but growing literature on the effects of

qualitative nonverbal communication on firm economic outcomes. Traditional accounting and finance research focuses on quantitative information included in mandatory and voluntary disclosures (i.e. the numbers), and more recently, the large amount of textual information accompanying those numbers. Overall, these studies find qualitative verbal communication to be incrementally useful to quantitative information in predicting a variety of firm outcomes (see Loughran and McDonald (2016) for a survey of the literature). In contrast, fewer scholars have explored the information sent through qualitative nonverbal communication (few exceptions are Blankespoor et al. 2017; Hobson et al. 2012; and Mayew and Venkatachalam 2012). This lack of evidence is despite the voluminous evidence from the psychology and communication literatures supporting the fundamental role of nonverbal cues in producing and communicating information (Burgoon et al. 2016). To the best of our knowledge, this study is one of the first to examine the role of perceived personality traits on important firm information sets (management forecasts), and economic outcomes more broadly (firm survival and firm valuation).

Third, our results are also of interest to a practitioner audience, since video content is becoming an increasingly relevant mean of communication between entrepreneurs and potential investors. Platforms like Kickstarter, Crowdcube, or AngelList largely include video communication to present investable projects (Clarke et al. 2018), often featuring the entrepreneurial team. Overall, these new forms of communication open new avenues for research that require cross-disciplinary approaches (including psychology, cognitive science, neuroscience, or communication disciplines) to underpin whether and how investors react differently to such communications.

3.2. Conceptual Background

3.2.1. Personality traits and nonverbal behavior

Individuals form impressions about others not only through verbal information but also through a range of nonverbal cues like gestures, body movement, eye gaze, facial expressions, and tone of voice (Ambady et al. 2000; Rosenthal et al. 1979). Together, these dynamic nonverbal cues transmit individual “expressive behavior” (Ambady and Rosenthal 1992; Blankespoor et al. 2017), and become important in forming more accurate perceptions of others (Ambadar et al. 2005).

Nonverbal communication has long been studied in association with individual personality traits. This association has captured the attention of social psychologists because nonverbal communication emerges many times unconsciously, making it suitable to express and maintain a given personality trait without the need to invoke it explicitly (Hall et al. 2005). For example, Gifford et al. (1985) find that an independent set of raters observing silenced-videos job interviews accurately rate individual social skills. Three nonverbal cues capture an individual's social abilities: rate of gesturing, time spent talking, and formality of dress. Borkenau and Liebler (1992) document that strangers infer personality traits like extraversion from individual's voice (e.g. powerful voices), static attributes (e.g. stylish hair or friendly expression), and dynamic behavior (e.g. arm swinging), but fail to find significant associations for other personality traits like agreeableness, culture, and emotional stability. Burgoon et al. (1990) find that perceived competence can be inferred from nonverbal cues like greater vocal and facial pleasantness and expressiveness. Similarly, Carney et al. (2005) document 35 nonverbal cues that are perceived differently between "high" versus "low" dominant individuals (e.g. expansive versus contractive body postures).

Taking all arguments together, the social psychology literature argues for nonverbal cues transmitting information about personality traits that shape entrepreneurs' behaviors and actions, and hence the development of the firm.

3.2.2. Personal characteristics and firm economic outcomes

A broad stream of literature has examined how managers' personal characteristics affect a variety of firm outcomes. Bertrand and Schoar (2003) highlight the importance of manager "fixed effects" (i.e. specific individual characteristics) in corporate-level investing, financing, and strategic decisions. Subsequent work has looked at the effect of managers' characteristics on investment decisions (Malmendier and Tate 2005, 2008), tax avoidance behavior (Dyreng et al. 2010), voluntary disclosure (Bamber et al. 2010), stock return variability (Adams et al. 2005), financial reporting risk (Davidson et al. 2015), and tone in regulatory filings and conference calls among others (Davis et al. 2015; Hendricks et al. 2018). These empirical studies proxy managers' personality traits such as overconfidence using structural variables including board characteristics (Adams et al. 2005), textual disclosures (Davis et al.

2015; Hendricks et al. 2018), and option exercising behavior (Hribar and Yang 2016; Schrand and Zechman 2012).

Fewer studies address personality traits directly measuring individual expressive behavior, despite recent evidence stressing the importance of nonverbal cues in corporate settings. Most analysts prefer to call or meet face to face with management teams when setting their estimates (Brown et al. 2015; Deloitte 2012), and brokerage houses use FBI and CIA agents to read nonverbal cues in analyst-manager interactions (Brown et al. 2015). Elliott et al. (2012) emphasize the importance of nonverbal cues in concluding that investors' behavior differ when the same corporate message is transmitted via text or video. Blankespoor et al. (2017) find that managers' expressive behavior provides information about leadership skills and ability to interact with stakeholders, which influences investors' perceptions of management, and therefore firm valuations. Jia et al. (2014) and Hobson et al. (2012) conclude that managers' facial masculinity and cognitive (vocal) dissonance are informative to detect financial misreporting. Mayew and Venkatachalam (2012) provide evidence that managerial vocal cues contain useful information about firm fundamentals. Overall, these studies underline the importance of individual qualitative nonverbal information (e.g. vocal tone, facial physiognomy, and gestures) to various corporate outcomes.

3.2.3. Personal characteristics in financing contexts

Our study explores entrepreneurs' perceived personality traits as a potential mechanism to anticipate financial forecast errors and firm overvaluations. We further explore the effect of such perceived personality traits on firm survival and actual investment decisions. By linking investor perceptions of the entrepreneur with firm economic outcomes, we assume that perceived individual traits translate into actual economic actions. Prior evidence supports this proposed association. Positive investors' assessments of entrepreneurs is associated with firm performance four years later (Huang and Pearce 2015); higher perceptions of borrower trustworthiness is related with better firm credit scores and lower default rates (Duarte et al. 2012), and more attractive borrowers with a higher likelihood of receiving a loan and pay less interest (Ravina 2019). We further argue that individual characteristics are more relevant in a young firm context, where founders concentrate most decision-making

power. Thus, we expect investor's perceptions of entrepreneurs' personality traits to be associated with financial forecast errors, proposed firm valuations, survival, and funding decisions.

We focus on those personality traits found to be associated with firms' financing activities, namely, passion, dominance, trustworthiness, competence, and attractiveness. The evidence on the association between passion and economic effects is mixed. Cardon et al. (2009) and Murnieks et al. (2016) document that business angels use entrepreneur's displayed passion (measured through nonverbal cues like energetic body movement, animated facial expressions, and varied voice tone) as a factor in their investment assessments. These authors argue that passion is related to tenacity in pursuing goals, inspirational leadership that attracts multiple stakeholders, and dedication and commitment to the venture (Cardon et al. 2009; Mitteness et al. 2012). In contrast, Chen et al. (2009) do not find any significant effect of passion on the decision to fund ventures. Actually, passion can produce response patterns that are obsessive, blind, or misdirected towards a narrow view of the venture or activity in question (Vallerand et al. 2003). This narrow scope has also been found to relate to forecasting activities (Kahneman and Lovallo 1993). These authors conclude that these type of individuals rely too much on the specifics of a case at hand (i.e. details of the venture and the obstacles to overcome) to build their forecasts rather than on a broader set of information including similar other cases or *base rate* information (i.e. objective predictors). This phenomenon has been termed the "inside view", and can limit the search for information, cloud rational decision-making, and lead to *rosy* forecasts (Cassar 2010; Kahneman and Lovallo 1993).

Similar to passion, dominance can lead to positive outcomes for the venture. Defined as someone who has or seek power, a dominant individual aims at gaining or maintaining influence over others (Schmid Mast and Cousin 2013). Dominant individuals are perceived as more assertive, proactive, confident, and attain more influence in social interactions than less dominant individuals (Anderson and Kilduff 2009; Vacharkulksemsuk et al. 2016). The importance of this personality trait in a financing context stems from the fact that more dominant or powerful individuals are more likely to acquire resources (Keltner et al. 2003), initiate negotiations in competitive scenarios (Magee et al. 2007), and improve performance on executive tasks like planning (Smith et al. 2008). Prior literature also links dominance to higher feelings of control (Fast et al. 2009), and willingness to engage in action (Galinsky et

al. 2003). While these findings support a positive effect of dominant individuals on firm economic outcomes, existing evidence also supports opposite arguments. Fast et al. (2012) find that overconfident decisions are more common in dominant (powerful) people, and that these decisions are more likely to lead to monetary losses. Similarly, Malmendier and Tate (2008) find that overconfident CEOs overestimate their ability to generate returns, overpaying for acquired companies and undertaking value-destroying mergers. Anderson and Galinsky (2006) observe that dominance (sense of power) increases optimism and riskier behaviors. Altogether, dominant individuals can impose both positive and negative effects on firm development.

On a physiological level, qualities related to more passionate and dominant individuals have been associated to higher testosterone and cortisol levels, two hormones that affect behavior. For instance, Schaal et al. (1996) find that 13 years old boys perceived as socially dominant show higher levels of testosterone than the less socially dominant. Mazur and Booth (1998) similarly report that high levels of testosterone encourage behavior intended to enhance one's status (i.e. dominance). On an asset trading game experiment, Cueva et al. (2015) conclude that cortisol positively affects risk-taking preferences directly, while testosterone does so by inducing overconfidence about future price increases. Also in a financial context, Coates and Herbert (2008) document a positive link between cortisol and testosterone levels and trading profitability and volatility. Furthermore, Jia et al. (2014) claim that testosterone levels can shape CEO facial masculinity and behavior (e.g. riskseeking, social status), which explains the observed association between financial misreporting and CEO facial masculinity. Overall, these two hormones have been documented to play a central role in the physiological and behavioral responses to stress, uncertainty, novelty, uncontrollability, or winning and losing (Coates and Herbert 2008); situations commonly found in the process of founding a business. We argue that actions and behaviors exerted by more dominant and passionate individuals can partly be explained through physiological characteristics; higher levels of testosterone and cortisol (even if only in specific situations) can shape individual's expectations about firm future prospects that would be reflected in more favorable financial forecasts.

Regarding trustworthiness, Maxwell and Lévesque (2014) find that entrepreneurs who receive more offers from investors exhibit a larger number of trust-building behaviors such as disclosure of private information and higher accuracy in information exchanges. Duarte et al. (2012) document positive impressions of

individual trustworthiness (as measured by MTurkers ratings of borrowers' photographs) being associated with higher probabilities of having loans funded and lower interest payments. According to the authors, this finding is consistent with individual's appearances signaling higher reputational capital that is difficult to manipulate and translates into positive firm outcomes. In contrast, and using the same peer-to-peer loan-granting context, Ravina (2019) fails to report the latter associations, implying that the former results may be subject to model specification. In an IPO setting, Blankespoor et al. (2017) also fail to find robust evidence that trustworthiness is priced into IPO firm valuation. They posit that other measures of trust (e.g. auditors) may mask the association between trustworthiness and valuation. The latter study also includes competence, finding robust results in its association with IPO price formation. Also in a corporate context, Graham et al. (2017) document that despite not showing better performance, more competent-looking CEOs receive higher compensation packages and place in bigger firms. Additionally, a well-known study in psychology shows that inferences of competence based solely on one-second exposure to facial appearances predict the outcomes of US congressional elections (Todorov et al. 2005). These findings together support the idea that competent-looking individuals can favorably shape perceptions of others (e.g. investors).

As for attractiveness, Brooks et al. (2014) document that firms managed by attractive males are more likely to be invested than those of non-attractive males. Blankespoor et al. (2017) find a positive and significant association between attractiveness and IPO firm valuation. Relatedly, a recent study in a peer-to-peer loan granting context reports that more attractive individuals are more likely to obtain a loan and pay lower interest rates (Ravina 2019). The study also documents that the less attractive perform better than the beautiful in default rates. Psychological studies posit that some of the positive outcomes related to attractive people comes from childhood, with educators having higher expectations on attractive kids and therefore devoting more time to them, fostering their confidence and social abilities (Hatfield and Sprecher 1986; Mobius and Rosenblat 2006). On the other hand, several studies report the presence of a beauty premium (or a *physical attractiveness stereotype*), by which people overestimate the abilities of more attractive individuals (Eagly et al. 1991; Feingold 1992), even when their performance has been shown to be as good as that of the less attractive peers (Graham et al. 2017; Mobius and Rosenblat 2006; Ravina 2019). Mobius and Rosenblat (2006) use a labor market experiment and find

that employers *wrongly* expect good-looking candidates to outperform less attractive ones, and hence, sign higher compensation packages with the more attractive. The study also finds that attractive people do not outperform the less attractive, a finding confirmed in Graham et al. (2017) and Ravina (2019). Overall, this evidence is inconclusive regarding how attractiveness can affect firm economic outcomes.

In light of the above findings, we take a more exploratory approach and do not state specific predictions as to how (sign) personality traits can affect financial forecast errors, firm valuation, survival, and investment outcomes. However, we argue that the preparation of those financial plans is entrepreneur-dependent and thus, subject to individual characteristics. Our study complements the set of available ex-ante information that early stage investors can use to mitigate potential business model uncertainties and (ex-ante) information problems.

3.3. Data

3.3.1. Sample

Our sample includes 245 entrepreneurial teams pitching their startups to an audience of about 100 investors between the years 2012 and 2015. These pitches take place at bimonthly investment forums organized by a European Business Angel Network. Each forum usually features between six and eight 10-minute entrepreneurs' presentations that the network selects out of between 15 to 25 candidates.[34] This community is one of the most active business angel (BA) and venture capital (VC) network in Europe and brings together entrepreneurs seeking outside funding and early stage investors. To present at the forum, selected startups fill out a standardized company profile that investors receive immediately before the forum takes place. The profile includes general information about the startup (e.g. brief description of the business and founding dates) and a series of open-ended questions: target market; competitive advantage; distribution and marketing strategy; key clients; strategic alliances; main competition; major milestones; strategic goals; and management team details. In addition, the profile also provides information on previous funding rounds (if any); main shareholders; business forecasts; and a summary of the current

[34] An informal committee makes sure that projects are not too early (just a power point) or late stage (already an established company) to meet the VC network investor base interests. Also, several industries are automatically discarded (e.g. arms, sex). As usual in these contexts, there can be certain selection towards Internet-based projects.

investment round (e.g. targeted amount to be raised, expected valuation, and usage of funds).

Table 3.1 describes the sample selection process. We discard four projects out of the original 245 companies because of serious recording deficiencies (e.g. entrepreneur is not displayed). We then merge projects to accounting information from the national accounting register (Bureau van Dijk's database). We lose 57 projects for which there are no official financial statements in the database. In addition, we could not obtain neither actual nor forecasted valid information on revenues or earnings for 29 startups, leaving our final sample at 155 firms (444 firm-year observations). In terms of industry composition, the majority of startups are Internet-based and operate mainly in the information and communication (e.g. SaaS) or the scientific sector (e.g. biotech or patent-related developments).

3.3.2. Entrepreneurs' personality traits and survey design

To obtain perceived personality traits measures, we asked independent respondents to rate the 155 videotaped entrepreneurs' presentations on five personal characteristics: passion, dominance, trustworthiness, competence and attractiveness. Additionally, we include openness in gestures to obtain a more direct measure of nonverbal display that has been found to affect individual's perceptions of others as well as access to resources (Vacharkulksemsuk et al. 2016). These same authors associate openness in gestures with dominance and power, which appear to be expressed with more expanded and open nonverbal postures such as widespread limbs, stretched torsos and the maximization of occupied space (Carney et al. 2005; Vacharkulksemsuk et al. 2016).

Following Blankespoor et al. (2017), we used content-filtered videos to isolate investors' perceptions of entrepreneurs from the verbal information conveyed throughout the presentation.[35] Thus, we capture a behavioral measure of perceived personality traits unrelated to the verbal content of the presentation (e.g. growth prospects, strategic alliances, or past performance), which also affects investor perceptions' of the entrepreneur. Next, we cut videos into 40-second clips that we then presented to 2,860 participants via the Turk Prime platform in November 2018.

[35] We use Audacity, a free audio software to content-filter videos. We use LowPass frequency filters at 200 Hz and 36dB octave to filter the voice. When required, we manually amplify the volume.

Prior research in social psychology validates the use of thin sliced videos to represent an entire behavioral sequence from which the individual is taken (Ambady and Rosenthal 1992; Ambady et al. 2006; Borkenau et al. 2004), and more recent studies rely on this technique to validate perceptions of management (Blankespoor et al. 2017).

The survey included four sections that respondents completed in about nine minutes on average. First, we asked respondents for their demographic characteristics: age, years of working experience, education, country of origin and ethnicity. Second, we randomly assigned one video (out of the 155) as a test video, asking respondents to adjust their sound levels and get them familiarized with the survey flow. Two questions followed this test video: a) number of speakers displayed in the clip, and b) a seven-point Likert scale assessment question on each speaker's personal characteristic (i.e. trustworthiness, attractiveness, competence, dominance, passion and openness in gestures). We discarded the ratings from this test section from the analysis. In an attempt to reduce concerns related to systematic within-participant response behavior, each respondent only rated three (out of six) randomly assigned characteristics, which were also displayed in random order. Third, the main section of the analysis reproduced the above test sequence for five randomly assigned videos, making sure that no video was displayed more than once to each participant. In addition, no respondent could progress to further sections of the survey until each video had been completely displayed. Fourth, in an attempt to validate the quality of the responses, we introduced two attention check questions by asking respondents to: a) click the "Trustworthy" option in a question that kept this personal characteristic fixed in the set of responses and, b) qualitatively explain the task they just performed.[36] As for the latter, we required the presence of some (root) words as proof of diligent participation (e.g. "speak", "body", "rate", "assess", "trait", "present" or "entrepreneur"). We dropped those respondents who failed the above attention check questions, those who took an excessive time to complete the survey (i.e. more than 15 minutes) and those who did not finalize the entire six video sequence. After the cleaning process, we obtained 1,772 valid unique respondents.

Table 3.2 reports demographics on the Turk Prime respondent base. The majority of respondents are female (58%) and are Caucasian (84%), and half of the

[36] Dennis et al. (2018) conclude that open responses (e.g. task description) work well in identifying respondent misbehavior and/or the presence of bots.

sample holds a college degree or more (52%). They generally accumulate around 10 to 29 years of working experience (40%) and are older than 50 years old (44%).

The output from the survey shows six significantly correlated behavioral variables. Table 3.3, Panel A reports correlations for the six variables, which are generally above 0.5 (with the exception of attractiveness) and significant at the 1% level. Thus, we reduce the dimensionality using principal component analysis with varimax rotation.[37] We summarize the six traits into three main components. While only one component has an eigenvalue higher than one, we decided to use three components in our analysis for the following reasons. Table 3.3, Panel B shows that the first component captures a high proportion of the original variance (i.e. 66%). Adding a second component increases the variance explained to 78% (and to 87% with the inclusion of the third component). Table 3.3, Panel C plots the original constructs into the first two components space: passionate, dominance and open in gestures load in component 1 (i.e. dots are far from the origin in the horizontal axis), and attractiveness, trustworthiness and competent load in component 2 (i.e. dots are far from the origin in the vertical axis). However, three differentiated clusters are visually identifiable, which indicates that the use of three components better reflects the original data. Accordingly, we run the analyses using three components. Table 3.3, Panel D reproduces Panel C analysis in table format using three components. Items that load on the first component are dominance, open in gestures and passion, three qualities that can make up presence (Cuddy et al. 2013). We name this factor "Presence". The second component includes trustworthiness and competence, attributes associated with high working standards and professionalism (we name this component as "Professional"). Finally, attractiveness loads alone in the third component (which is coherent with attractiveness being relatively less correlated to the rest of original variables, see Panel A of Table 3.3), so we name the component "Attractive".[38]

[37] We run the Kaiser-Meyer-Olkin (KMO) test of adequacy. This statistic indicates the proportion of variance that the underlying factors can cause on the original variables. High values (i.e. close to 1) indicate that a reduction in the number of components is adequate, while values lower than 0.5 discard the use of factor reduction. The untabulated KMO statistic in our data report values higher than 0.8 in all of the six original variables, hence supporting the use of principal component analysis.

[38] We also run our main analysis using one and two components; results are reported in Table A2.

3.3.3. Dependent variables

Our dependent variables are revenue and earnings forecast error (*Forecast_Rev_Err* and *Forecast_Inc_Err* respectively), and firm proposed valuations (*Val_indic*). We measure revenue forecast error using the definition in Cassar (2010), which compares entrepreneurs' *ex ante* expectations with actual realizations and scales the difference by the sum of both.

$$Forecast\_Rev\_Err = (\text{Forecast} - \text{Actual}) / (\text{Forecast} + \text{Actual}) \quad (3.1)$$

The main advantage of this measure is its range, comprised between -1 (extremely pessimistic forecasts) and +1 (extremely optimistic). A revenue forecast error of -1 indicates a startup that forecasted €0 revenues but ended up generating some revenues (i.e. pessimistic forecasts). Likewise, forecast error of +1 indicates a startup that does not have actual revenues even if its revenue forecast was positive (i.e. optimistic forecasts). The measure equals zero when forecast revenues equal actual revenues (i.e. no error). This measure is particularly suitable to our interests since it allows for comparisons of personality traits with positive, neutral or negative forecasting errors. Figure 1 presents the frequency distribution of this variable. Notably, in the one-year-ahead forecast data we observe a peak at around zero (i.e. no forecast error), which can be explained by entrepreneurs being more accurate in short term horizons and some presentations being held close to the fiscal year end (where less errors should be observed). The peak disappears when the sample extends to a forecast horizon of two or more years. This logic is consistent with prior literature on young firms' management forecasts (Armstrong et al. 2007). Consequently, we extend the main analysis by splitting the sample into short (one-year) and long term forecast errors (two or more year forecasts) and by adding a control that measures the number of days left between the presentation day and the fiscal year end (*Days_left*).

Forecasted and actual operating income (earnings) can often show negative amounts in startups, therefore distorting the logic of the above measure (only suitable for zero or positive amounts). To obtain a proxy for operating income forecast error, we compute the difference between the forecasted and actual income and scale it by revenues (size). The idea being that, a deviation of €5,000 in a €1M revenue company shows a relatively good forecast (i.e. relatively small prediction error), while the same deviation in a €10,000 revenue firm reflects a rather "bad" prediction. This measure is negative when earnings forecasts are lower (i.e. more pessimistic) than actual, and

positive otherwise. Untabulated statistics indicate the presence of several outliers (mean value of 207.05; p90 value of 27.57; and a minimum and maximum value of -8,559 and 65,776 respectively), hence, we construct a new variable *Forecast_Inc_Err* that splits the above measure into 5 quantiles (from 1—more pessimistic earnings forecasts to 5—more optimistic).

Next, we examine entrepreneurs' firm proposed valuation (as featured in the profile documentation that investors receive at the start of each forum). In particular, we seek to identify those valuations that appear to be overpriced, and relate them to the entrepreneur's personality traits. We acknowledge that determining whether a startup is under/overvalued is challenging, so we compare the proposed valuation against a benchmark. We set the benchmark to be the in-sample mean of the ratio between firm valuation (the valuation amount) and revenues by financing round. Expressing the valuation amount as a multiple of the firm's revenues is meaningful in a startup context, since revenues generally validate the product and the company business model more broadly. If a given project shows a valuation/revenues ratio higher than the mean for a given round, then we classify that observation as an overvalued valuation (See Table 3.4, Panel C).

Finally, we test the association between entrepreneur's personality traits, firm survival, and investment outcome. The national accounting register reports the status of a company in its last available annual filings. We construct an indicator variable that equals 1 for active companies (104 out of 155) and 0 otherwise (i.e. dissolution, insolvency procedures, winding up or provisional deregistration Bureau van Dijk's categories). We also record whether each startup received financing from the investor community.

3.3.4. Descriptive statistics

Table 3.4, Panel A presents descriptive statistics for the one-year-ahead forecast sample. In line with prior research (see Armstrong et al. 2007; Cassar 2010), entrepreneurs report favorable revenue forecasts, with positive mean and median one-year-ahead forecasting errors of 0.44 and 0.51 respectively, even if one-year forecast contains the most available information (e.g. signed clients or platform current metrics). This optimistic error is also present in the long-term sample (Panel B) with a mean of 0.74 and median of 0.84.

Operating income forecast error is measured between 1 (more pessimistic earnings forecasts) and 5 (optimistic). The mean for the one-year-ahead sample is 2.31 (Panel A) and 3.74 for the longer-term income forecasts (Panel B). This statistic is in line with more positive income forecast errors (optimism) in longer time horizons where information is less readily available.

The third outcome variable of interest is the proposed firm valuation; a mean of 0.15 indicates few entrepreneurs overvalue their firm (out of the 125 companies that report this statistic, we classify 19 as overvalued). If any, this variable captures a conservative measure of firm overvaluation. As for survival, we show that 68% of the firms are still alive as of the last available annual report. Finally, the investment indicator variable shows that 26% companies received financing after the forum.

Regarding personal characteristics, we standardize all measures to perform the principal component analysis, and hence report a mean of zero and a standard deviation of one. All three components behave similarly, which is consistent with the original variables being similarly distributed (with mean values around 4 to 4.5 and standard deviations between 0.4 to 0.7, see Table 3.3, Panel A).

Finally, we also include a set of control variables that may influence the association between personal characteristics and forecast error, firm valuation, survival and investment. These control variables include firm age (mean of 32.65 months), size (the average startup firm has five employees), presence of prior outside financing (i.e. business angels, venture capital, accelerators or lenders), amount of capital requested and financing round. We also control for team characteristics such as proportion of males in the entrepreneurial team and percentage of members with prior industry and/or startup experience.

3.4. Empirical results

To test the effect of entrepreneurs' personality traits on our dependent variables, we estimate the following pooled OLS and logit (where applicable) specification:

$$\textit{Outcome variable} = \alpha + \textit{Personality\_trait}\ \beta + X\eta + \delta + \gamma + \varepsilon \qquad (3.2)$$

Outcome variable is one of the dependent variables (i.e. revenue and income forecast error for firm *i* in year *t*, firm overvaluation at forum date, survival, and investment outcome). *Personality_trait* includes our variables of interest resulting from the principal component analysis: presence, professional, and attractive. *X* represents a set

of control variables. Appendix A1 describes all variables. The model also includes year and industry fixed effects (δ and γ respectively), and clustered standard errors at industry and firm level.

3.4.1. Personality traits and firm forecasting behavior

Table 3.5 reports the association between the three components of personality traits and firm forecasting errors. *Presence*, which includes ratings on passion, dominance, and openness in gestures, is positive and significantly associated with revenue forecast errors (coefficient of 0.036 and t-statistic of 4.08), both in the overall sample and after the split between the short (column 2) and long run projections (column 3). The effect of *Presence* in forecasted income (columns 4 to 6) only becomes significant in the short run (coefficient of 0.140 and t-statistic of 2.56), but the direction (sign) and magnitude of the other coefficients are comparable to those observed in the revenue forecast errors models. These associations are consistent with passionate individuals being more obsessive or misdirected towards a narrow view of the venture (Vallerand et al. 2003). Kahneman and Lovallo (1993) term this shortsighted approach the "inside view", and claim that individuals who overly rely on the specifics of a case at hand (i.e. the company) tend to limit the search for information as well as rational decision-making, therefore producing higher forecast errors. Likewise, dominant and passionate individuals also possess higher tolerance to risk (Anderson and Galinsky 2006), feelings of control (Fast et al. 2009) and willingness to engage in action (Galinsky et al. 2003), traits that can help to explain the positive associations. An alternative explanation for these findings beyond the behavioral argument is rooted in biological characteristics, with higher levels of testosterone and cortisol observed in passionate and dominant individuals (Coates and Herbert 2008; Cueva et al. 2015; Mazur and Booth 1998; Schaal et al. 1996).

Attractiveness shows a positive and significant association with both revenue and earnings forecast errors (with the exception of short-term revenue forecast errors in column 2). This finding supports the argument that attractive people can better develop non-cognitive skills important for economic and social success from as early as childhood, with teachers expecting better looking kids to outperform the others, hence devoting more attention to them (Hatfield and Sprecher 1986; Heckman 2000). This preferential treatment in return builds confidence (Mobius and Rosenblat 2006),

which raises high expectations about firm's future prospects (i.e. higher forecast errors).

The *Professional* component has no effect on forecast errors. Related studies also fail to find an association between trustworthiness (one of the variables in this component) and economic outcomes. For instance, in a loan context, Ravina (2019) finds no effect of trustworthiness on the likelihood of receiving a loan, and argue that other information included in the model may capture the effect of this personality trait. Similarly, Blankespoor et al. (2017) also fail to find a robust significant association between CEO perceived trustworthiness and IPO firm valuation. They attribute this weak result to other trust-related control variables (e.g. audits) superseding the effect of trustworthiness on valuation. We reason that having prior startup and industry experience or having been able to raise financing (e.g. VCs) may proxy for individual competence and trustworthiness, hence capturing the effect of the *Professional* construct.

Finally, various control variables have a significant effect on revenue and earnings forecast errors. First, size (number of employees) has a consistent negative association with revenue forecast errors (Table 3.5, columns 1 to 3), but a positive and significant coefficient for the one-year earnings forecast errors (column 5). This finding suggests that firm growth (proxied by variables such as revenues) may be easier to forecast for larger firms, while earnings contain additional costing information that can still be difficult to project at initial stages of the firm (where larger firms may experience larger variability in output volumes). Second, debt is positively related to revenue (column 1 and 2) but not to earnings forecast errors (columns 4 to 6), which indicates that higher availability of cash can be associated with higher growth expectations but not profitability (Epure and Guasch 2019). Third, several governance variables including the presence of venture capital and the number of previous financing rounds (which implicitly identifies the presence of professional investors) are negatively associated to both types of forecast errors. This finding is consistent with prior studies indicating that these agents place accounting and control mechanisms to institute better governance within the firm (Davila and Foster 2007). Finally, Table 3.5 also indicates that having industry experience is positively associated with both revenue and earnings forecast errors. A potential explanation is that entrepreneurs coming from an established corporation within the same industry tend to think in bigger amounts (e.g. amounts negotiated in the prior corporate

position) and overlook the difficulties associated with starting up a business. This finding is consistent with related work analyzing entrepreneurs' expectations on operational and growth outcomes (Cassar 2010).

3.4.2. Personality traits, firm valuation, survival, and investment outcome

Table 3.6 reports the association between personality traits and firm valuations, survival, and investment outcomes. First, we find that entrepreneurs with higher *Presence* are more likely to overvalue their firms (column 1), setting valuations with multiples over revenues that exceed the mean multiple of its peers in the same round. This finding supports the "inside view" argument in that more passionate and dominant individuals overlook a broader set of information (e.g. similar company valuations as theirs) that would help them set more comparable to its peers valuations (Kahneman and Lovallo 1993; Vallerand et al. 2003). We also find that higher *Presence* is associated with lower survival rates (column 2). Prior literature suggests that dominant individuals better tolerate riskier actions (Anderson and Galinsky 2006), and are overconfident about their firm's ability to generate returns (Malmendier and Tate 2008), hence making decisions that can lead to monetary losses (Fast et al. 2012). Furthermore, the physiological characteristics of the passionate and dominant, with increased levels of testosterone and cortisol, would also lend support to the above findings and argumentation. Altogether, it seems plausible that higher presence individuals are more ready to take actions (i.e. burn cash) that severely affect the wellbeing of the firm.

Paradoxically and despite higher valuations and lower survival rates, investors are more likely to fund companies managed by higher *Presence* entrepreneurs (Table 3.7, column 3). We argue that dominant and passionate individuals are perceived to be associated with positive outcomes like tenacity in pursuing goals, inspirational and effective leadership, and dedication to the venture (Cardon et al. 2009; Chen et al. 2009; Mitteness et al. 2012); qualities that may attract prospective investors and stakeholders more generally. Lending support to a behavioral argumentation, these results suggest that investors hold slow-to-adjust misperceptions of entrepreneurs by investing in ventures that show lower survival rates and higher valuations.

Attractiveness is also positively associated with a higher likelihood of investment (Table 3.7, column 3), which is coherent with the *physical attractiveness stereotype*. We argue that people overestimate the qualities of attractive individuals (e.g. intelligence, health, social skills), even when non ex-post performance differences have been found between the attractive and the non-attractive (Eagly et al. 1991; Feingold 1992; Graham et al. 2017; Mobius and Rosenblat 2006; Ravina 2019). Our findings are in line with the above logic in that investors are more likely to fund an attractive entrepreneur that do not demonstrate higher performance in survival rates (coefficient of -0.220 and t-statistic of -0.79).

Finally, several control variables are also significant in Table 3.6. Larger, older, and companies managed by experienced entrepreneurs are less likely to propose valuations above the mean revenue multiple (column 1). Furthermore, column 2 shows that the presence of business angels and having industry experience increase the likelihood of survival. In contrast, accelerators show a negative correlation with survival, which may be explained by these agents being less selective and generally operating in earlier stages than business angels or VCs. Consistent with prior literature, column 3 reports that large companies, those with outside investors (i.e. VCs and BAs), higher levels of debt, and more proportion of males are more likely to obtain financing (Brooks et al. 2014; Davila and Foster 2007; Epure and Guasch 2019). Lastly, we find that prior startup experience is associated with a lower probability of investing. If most startups fail, investors might be associating past experience with lack of entrepreneurial skills.

3.5. Conclusions

Investors face high uncertainties and information problems with entrepreneurs at early stage investments. To insulate against such problems, investors demand ex-ante information that can be used for contract design and ex-post monitoring of firm activities. This paper focuses on ex-ante information. We analyze how perceived personality traits can shape management-reported information prior to the investment event, and put special emphasis on firm financial projections and valuation. We further explore the effect of such personal traits on firm survival and actual investment decisions. We find that perceived presence (a component capturing passionate, dominance and openness in gestures) is positively associated with revenue

and earnings forecast errors, firm overvaluations, and the likelihood of being invested. We also find that attractive people are also more likely to receive funding, yet they produce higher forecast errors. We attribute these findings to passionate, dominant, and attractive individuals being more confident about firm's future prospects, which easily limits the search for information and clouds rational decision-making. We additionally posit that physiological characteristics of the entrepreneur can help to explain our results, with higher levels of testosterone and cortisol (two hormones that affect behavior) being found in higher presence and attractive individuals. Altogether, our study documents that individual personality traits affect both entrepreneurs' information preparation processes and firm outcomes (i.e. survival and the likelihood to receive equity injections), suggesting that investors could factor in those perceived personality traits when hedging against potential information problems and business model uncertainties.

Table 3.1. Final sample

Panel A. Sample selection	Firms	Firm-year observations
Videotaped projects (between October 2011 and March 2016)	245	
Bad recordings	-4	
Accounting information available (BvD)	-57	
Revenue and earnings not available (actual or forecasts)	-29	
Number of firms	155	444

Panel B. Industry distribution (based on primary CNAE)	Firms	%
Administrative and auxiliary activities	10	6.45
Education	1	0.65
Financing and insurance activities	2	1.29
Health and Social Services	4	2.58
Information and communication	53	34.19
Manufacturing	13	8.39
Others	1	0.65
Real Estate	2	1.29
Scientific and liberal activities	44	28.39
Wholesale and retail	25	16.13
Total	**155**	**100.00**

Panel A describes our sample composition. While the one-year forecast specifications include 155 firms (observations), the long-term forecasts (i.e. two or more years) use 289 firm-year observations (provided by the 155 firms). Panel B details our sample composition by industry based on primary CNAE codes. Table A1 describes all variables.

Table 3.2. Descriptive statistics Turk Prime respondents

	Frequency	Percent
Gender		
Male	744	41.99
Female	1,028	58.01
Total	**1,772**	**100.00**
Working experience		
< 10 years	470	26.52
10 - 29	711	40.12
>=30	591	33.35
Total	**1,772**	**100.00**
Age		
< 30 years old	307	17.33
30 - 49	682	38.48
>=50	783	44.19
Total	**1,772**	**100.00**
Education		
Some high school but no diploma	27	1.52
High school graduate or equivalent	277	15.63
Trade, technical or vocational training	175	9.88
Some college but no diploma	378	21.33
College graduate	611	34.48
Some postgraduate work but no diploma	61	3.44
Postgraduate degree	243	13.71
Total	**1,772**	**100.00**
Ethnicity		
African American	97	5.47
Asian	41	2.31
Caucasian (White)	1,490	84.09
Hispanic	103	5.81
Other	41	2.31
Total	**1,772**	**100.00**

Table 3.2 provides demographic characteristics of 1,772 respondents that successfully answer the survey. A description of the screening process to obtain such 1,772 valid respondents is provided in Data section.

Table 3.3. Principal Component Analysis

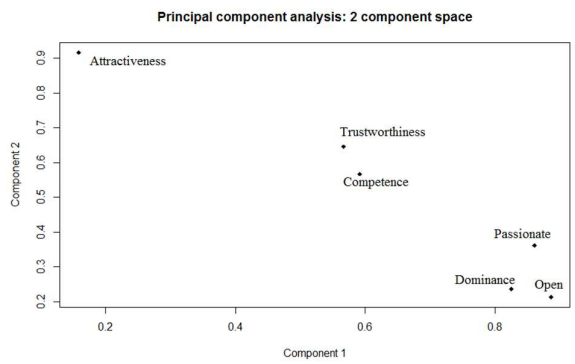
Panel A. Correlation table for personality measures

	1	2	3	4	5
Trustworthiness	1.00				
Competence	0.69	1.00			
Attractiveness	0.57	0.47	1.00		
Dominance	0.53	0.58	0.44	1.00	
Passionate	0.69	0.66	0.49	0.76	1.00
Open gestures	0.67	0.60	0.39	0.70	0.82

Panel B. Principal Component Analysis

	Eigenvalue	% of variance explained	Cumulative % of variance explained
Component 1	3.96	0.66	0.66
Component 2	0.72	0.12	0.78
Component 3	0.51	0.09	0.87
Component 4	0.38	0.06	0.93
Component 5	0.27	0.04	0.97
Component 6	0.16	0.03	1.00

Panel C. Factor loadings (2 components required)



Panel D. C loadings (3 components)

	Factor 1	Factor 2	Factor 3
Trustworthiness		0.804	
Competence		0.822	
Attractiveness			0.933
Dominance	0.873		
Passionate	0.780		
Open in gestures	0.793		

Table 3.3 describes the process to perform the principal component analysis. Panel A presents the correlation matrix of the original six personality traits variables. All correlations are significant at a 1% level. Panel B describes the output from the principal component analysis, showing eigenvalues for each component, and the proportion of the original (variables) variance explained. Despite showing an eigenvalue lower than 1, the use of the second component significantly improves the original explained variance from 66% to 78%. Panel C depicts the factor loadings when two components are specified in the principal component analysis: passionate, dominance and open in gestures load in component 1 (i.e. far from 0 in the horizontal axis), and attractiveness, trustworthiness and competent load in component 2 (i.e. far from 0 in the vertical axis). However, graphically, the presence of three clusters naturally appear, indicating that the use of three factors can fit better the original data. Finally, Panel D reports the same factor loadings when using three components, which are well represented in each factor, with loadings greater than 0.75.

Table 3.4. Descriptive statistics

Panel A. Descriptive statistics (observations first year)

Variable name	N	Mean	Std. dev	Min	Max	p25	p50	p75
Forecast_Rev_Err	155	0.44	0.41	-1	1	0.11	0.51	0.78
Forecast_Inc_Err	153	2.31	1.34	1	5	1	2	3
Val_indic	125	0.15	0.36	0	1	0	0	0
Active	147	0.68	0.47	0	1	0	1	1
Invest	155	0.26	0.44	0	1	0	0	1
Days_left	155	191.97	105.67	16	346	85	204	283
Presence	155	0	1	-3.58	2.15	-0.57	0.07	0.71
Profession	155	0	1	-2.56	2.12	-0.67	0.01	0.69
Attractive	155	0	1	-2.58	3.12	-0.73	-0.01	0.56
Firm age	155	32.65	31.05	0	243	16	27	37
Employees	155	4.97	5.00	1	38	2	3	7
VC	155	0.14	0.35	0	1	0	0	0
BA	155	0.48	0.50	0	1	0	0	1
Accelerator	155	0.08	0.28	0	1	0	0	0
Debt	155	0.15	0.36	0	1	0	0	0
Log(Capital)	155	12.60	0.79	10.82	15.61	12.21	12.61	13.12
Round number	155	1.22	1.05	0	5	0	1	2
Male ratio	155	0.82	0.24	0	1	1	1	1
Industry experience ratio	155	0.60	0.41	0	1	0	1	1
Startup experience ratio	155	0.27	0.32	0	1	0	0	1

Panel B. Descriptive statistics (observations second year and more)

Variable name	N	Mean	Std. dev	Min	Max	p25	p50	p75
Forecast_Rev_Err	289	0.74	0.32	-0.99	1.00	0.67	0.84	0.95
Forecast_Inc_Err	289	3.74	1.25	1	5	3	4	5
Employees	289	8.94	10.87	1	103	3	5	12

Panel C. Descriptive statistics (Rounds of funding)

Variable name	Frequency	Percentage	Cumulative
Round 0	53	34.2	34.2
Round 1	29	18.7	52.9
Round 2	63	40.7	93.6
Round 3 or more	10	6.4	100
Total	155	100	

Panel A reports statistics from time invariant variables taken at forum date (e.g. having been invested by a VC, BA or accelerator at forum date), or individual characteristics (e.g. personality ratings or entrepreneurs characteristics). Panel A also shows first year observations of time variant variables (e.g. first year revenue forecast errors), while second or more year observations are summarized in Panel B. Note that *Forecast_Inc_Err* shows a lower number of observations due to one company having 0 revenues (denominator). Furthermore, *Val_indic* (*Active*) shows only 125 (147) observations due to entrepreneurs not reporting their company valuations (and official registers not reporting company status). Panel C provides descriptive statistics on the financing history of the companies. Table 3.A1 describes all variables.

Table 3.5. Revenue forecast errors

	All sample	Sample split		All sample	Sample split	
		1 year forecast	2+ year forecast		1 year forecast	2+ year forecast
	(1) Forecast_ Rev_Err	(2) Forecast_ Rev_Err	(3) Forecast_ Rev_Err	(4) Forecast_ Inc_Err	(5) Forecast_ Inc_Err	(6) Forecast_ Inc_Err
Presence	0.036***	0.048**	0.027***	0.066	0.140**	0.024
	(4.08)	(1.98)	(2.68)	(1.15)	(2.56)	(0.34)
Professional	0.004	0.006	0.018	-0.043	0.032	-0.089
	(0.19)	(0.21)	(0.77)	(-0.47)	(0.22)	(-0.97)
Attractive	0.046*	0.023	0.046***	0.152***	0.187***	0.117***
	(1.87)	(0.65)	(2.99)	(11.35)	(3.55)	(3.31)
Days_left		0.001***			-0.002***	
		(3.86)			(-6.05)	
Firm age	-0.001	-0.000	-0.001*	-0.002	-0.002	-0.002
	(-1.28)	(-0.16)	(-1.90)	(-1.16)	(-1.52)	(-1.12)
Empl	-0.005***	-0.013*	-0.008***	0.008	0.051**	-0.001
	(-6.44)	(-1.83)	(-7.81)	(0.79)	(2.44)	(-0.14)
VC	-0.077***	-0.097	-0.017	-0.357*	-1.022***	-0.118
	(-2.67)	(-1.41)	(-0.69)	(-1.94)	(-3.53)	(-0.70)
BA	0.028	-0.108**	0.071	0.720***	1.045***	0.553***
	(0.58)	(-2.14)	(1.45)	(4.58)	(4.16)	(6.55)
Accelerator	-0.034	0.020	-0.033	0.446**	0.772**	0.540**
	(-0.31)	(0.25)	(-0.24)	(2.07)	(2.86)	(2.29)
Debt	0.046**	0.147***	0.018	-0.096	-0.342	0.111
	(2.04)	(3.90)	(0.60)	(-0.76)	(-1.21)	(0.92)
Log(Capital)	-0.026*	-0.030	0.008	-0.045	-0.042	-0.040
	(-1.79)	(-0.56)	(0.26)	(-0.29)	(-0.25)	(-0.29)
Round number	-0.041*	0.014	-0.056**	-0.293***	-0.135	-0.392***
	(-1.78)	(0.62)	(-2.54)	(-4.47)	(-1.14)	(-8.56)
Male ratio	-0.022	-0.043	-0.055	-0.325	-0.359	-0.504*
	(-0.26)	(-0.40)	(-0.70)	(-1.37)	(-1.44)	(-1.70)
Industry experience ratio	0.085***	-0.037	0.111***	0.602***	0.398	0.630**
	(5.64)	(-1.24)	(3.45)	(3.10)	(1.46)	(1.99)
Startup experience ratio	-0.092	-0.149	-0.058	-0.646***	-0.549*	-0.554
	(-0.71)	(-0.99)	(-0.42)	(-3.34)	(-1.66)	(-1.31)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	444	155	289	442	153	289
R-squared	0.262	0.352	0.302	0.311	0.321	0.273

Table 3.5 reports OLS regression coefficients from estimating equation (1) with *Forecast_Rev_Err* (columns 1 to 3) and *Forecast_Inc_Err* (columns 4 to 6) as dependent variables. Columns 1 and 4 use the overall pooled sample (with standard errors clustered at industry and firm level), while columns 2, 3, 5 and 6 split the sample into one-year revenue forecast errors, and two or more year forecasts for both dependent variables respectively (standard errors clustered at industry level). Observations drop from N=444 (155) to N=442 (153) in column 5 (6) due to one company reporting €0 revenues (denominator of the *Forecast_Inc_Err* measure). Table 3.A1 defines all variables. *p<0.10, **p<0.05, ***p<0.01

Table 3.6. Firm valuation, survival and actual investment

	(1) Val_indic	(2) Active	(3) Invest
Presence	0.308***	-0.361***	0.541**
	(3.14)	(-2.95)	(2.51)
Professional	0.289	0.074	0.117
	(0.85)	(0.36)	(0.48)
Attractive	0.022	-0.220	0.396*
	(0.05)	(-0.79)	(1.76)
Firm age	-0.049***	0.006	0.002
	(-4.69)	(1.02)	(0.44)
Empl	-0.340***	-0.056	0.103**
	(-3.84)	(-1.12)	(2.08)
VC	-0.267	0.599	1.775***
	(-0.23)	(0.88)	(3.28)
BA	-0.780	0.469**	0.773**
	(-1.31)	(2.39)	(2.10)
Accelerator	-0.202	-2.064***	-0.862
	(-0.20)	(-4.10)	(-1.61)
Debt	0.476	0.345	1.078***
	(0.48)	(0.63)	(3.97)
Log(Capital)	1.957***	0.398	-0.158
	(2.80)	(1.61)	(-0.61)
Round number	0.470*	-0.166	-0.074
	(1.90)	(-0.84)	(-0.38)
Male ratio	0.162	-1.539*	1.922**
	(0.29)	(-1.71)	(2.55)
Industry experience ratio	-0.438	0.706***	1.429
	(-0.44)	(2.96)	(1.62)
Startup experience ratio	-2.437**	0.339	-2.291***
	(-2.16)	(0.96)	(-6.91)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Observations	125	147	155
Pseudo R-squared	0.349	0.283	0.259

Table 3.6 reports logit regression coefficients for: firm (over)valuation (column 1), firm survival (column 2), and actual investment decision (column 3). *Val_indic* is a variable that takes the value of 1 when the entrepreneur sets a valuation that is higher than the mean of equal rounds valuations (where valuation is defined as the entrepreneur's proposed firm value over actual revenues). *Active* takes the value of 1 for firms that are still active in the last available annual filing. *Invest* is set to 1 if the company received investment associated with the forum. In column 1, observations are reduced from 155 to 125 because 30 entrepreneurs do not report valuation information at forum date. Column 2 reports 147 observations since BvD database shows eight missing values in the "status" variable. Table 3.A1 defines all variables. Standard errors clustered at industry level. *p<0.10, **p<0.05, ***p<0.01

Figure 3.1. Revenue forecast error variable distribution across forecast horizons

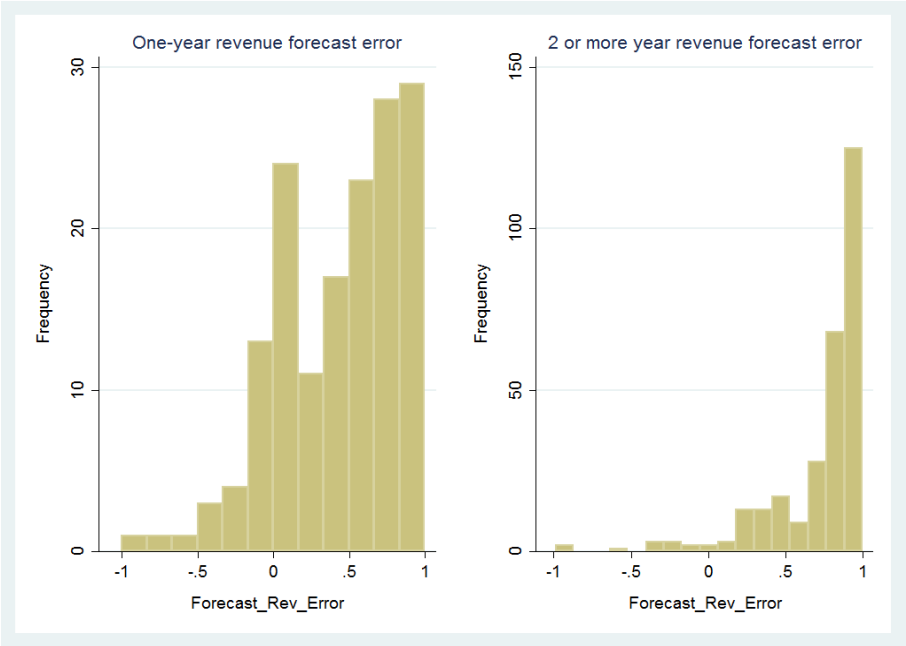


Figure 3.1 plots the revenue forecast error variable distribution for the short term one-year forecasts (left graph; N=155) and the long term year forecasts (right graph; N=289). A value of 0 represents no forecast error, while extremely optimistic (pessimistic) forecasts are represented with the value of +1 (-1).

3.6. Supplementary appendix

Table 3.A1. Variable definitions

Variable name	Description
Dependent variables	
Forecast_Rev_Err	Revenue forecast error = Forecasts - Actual / (Forecast + Actual)
Forecast_Inc_Err	Value of [(Forecasts – Actual) / Revenues] assigned into 5 quantiles: Lower (higher) quantile represents the more pessimistic (optimistic) earnings forecasts
Val_indic	1=firm valuation is above the mean firm valuation over revenues by financing round; 0=otherwise
Active	1=firm is still active in the last available register at the BvD database; 0=dissolved
Invest	1=Investment received by investors in the Business Angel Network; 0=otherwise
Main independent variables	
Presence	PCA factor resulting from entrepreneur's ratings on passion, open in gestures, and dominance
Professional	PCA factor resulting from entrepreneur's ratings on trustworthiness and competence
Attractive	PCA factor resulting from entrepreneur's ratings on attractiveness
Control variables	
Days_left	Number of days until current year December 31st
Firm age	Age (in months)
Empl	Number of employees
VC	Indicator variable that equals 1 with Venture Capital presence; 0 otherwise
BA	Indicator variable that equals 1 with Business Angel presence; 0 otherwise
Accelerator	Indicator variable that equals 1 with business Accelerator presence; 0 otherwise
Debt	Indicator variable that equals 1 with debt presence; 0 otherwise
Log(Capital)	Logarithm of capital solicited to investors
Round number	Financing round number
Male ratio	Percentage of males in entrepreneurial team
Industry experience ratio	Percentage of people with prior industry experience in entrepreneurial team
Startup experience ratio	Percentage of people with prior startup experience in entrepreneurial team

Table 3.A2. One and two component analysis

	One component					Two components				
	(1) Forecast_ Rev_Err	(2) Forecast_ Inc_Err	(3) Val_indic	(4) Active	(5) Invest	(6) Forecast_ Rev_Err	(7) Forecast_ Inc_Err	(8) Val_indic	(9) Active	(10) Invest
Component 1	0.042*	0.068	0.415***	-0.300*	0.572*	0.026**	0.013	0.385	-0.256**	0.417**
	(1.73)	(0.89)	(2.75)	(-1.83)	(1.85)	(2.45)	(0.17)	(1.00)	(-2.46)	(1.84)
Component 2						0.043	0.125***	0.147	-0.175	0.392
						(1.19)	(4.03)	(0.44)	(-0.55)	(1.16)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Model	OLS	OLS	Logit	Logit	Logit	OLS	OLS	Logit	Logit	Logit
Observations	444	442	125	147	155	444	442	125	147	155
R-squared (OLS) / Pseudo R-squared (Logit)	0.255	0.302	0.348	0.274	0.249	0.258	0.306	0.348	0.274	0.247

Table 3.A2 reproduces the analysis using one and two components resulting from the principal component analysis. Table 3.A1 defines all variables. Standard errors are clustered at firm and industry level in columns 1, 2, 6 and 7, and at industry level in columns 3 to 5 and 8 to 10). *p<0.10, **p<0.05, ***p<0.01

Table 3.A3. Revenue forecast errors and entrepreneur's personality traits (original variables)

	One-year revenue forecast error						Two or more-year revenue forecast error					
	(1) Forecast_ Rev_Err	(2) Forecast_ Rev_Err	(3) Forecast_ Rev_Err	(4) Forecast_ Rev_Err	(5) Forecast_ Rev_Err	(6) Forecast_ Rev_Err	(7) Forecast_ Rev_Err	(8) Forecast_ Rev_Err	(9) Forecast_ Rev_Err	(10) Forecast_ Rev_Err	(11) Forecast_ Rev_Err	(12) Forecast_ Rev_Err
Trustworthiness	-0.01						0.10					
	(-0.08)						(1.30)					
Attractiveness		0.07						0.09***				
		(0.84)						(2.77)				
Competence			0.09						0.06			
			(1.26)						(1.44)			
Dominance				0.06						0.07		
				(1.28)						(1.44)		
Passionate					0.10**						0.06**	
					(2.01)						(2.30)	
Open gestures						0.069**						0.044*
						(2.51)						(1.81)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	155	155	155	155	155	155	289	289	289	289	289	289
R-squared	0.267	0.275	0.274	0.272	0.287	0.277	0.293	0.299	0.285	0.291	0.290	0.286

Table 3.A3 reports OLS regression coefficients from estimating equation (1) for the six original personality traits obtained from Turk Prime's respondents. Each trait is presented separately to avoid multicollinearity issues. Dependent variable *Forecast_Rev_Err* is the revenue forecast error. Table 3.A1 defines all variables. Standard errors are clustered at industry level. *p<0.10, **p<0.05, ***p<0.01

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